Multi-Sensor Analysis of Global Daytime and Nighttime Urban Heat Islands

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Annemarie Schneider[3], Tom Milliman[1], Jingfeng Xiao[1]

1. University of New Hampshire, Durham

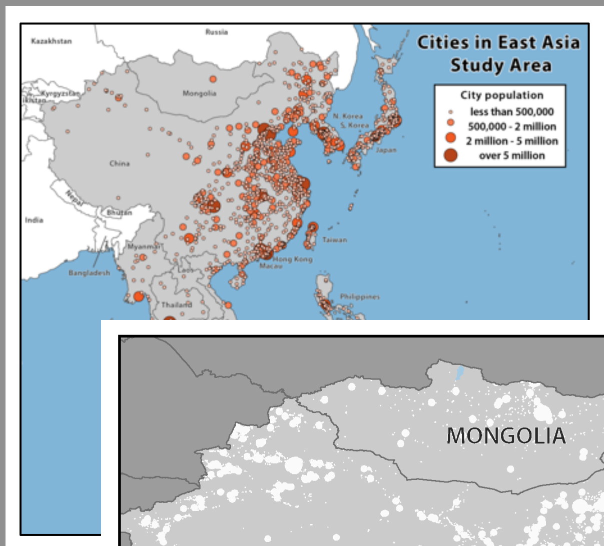
2. Boston University

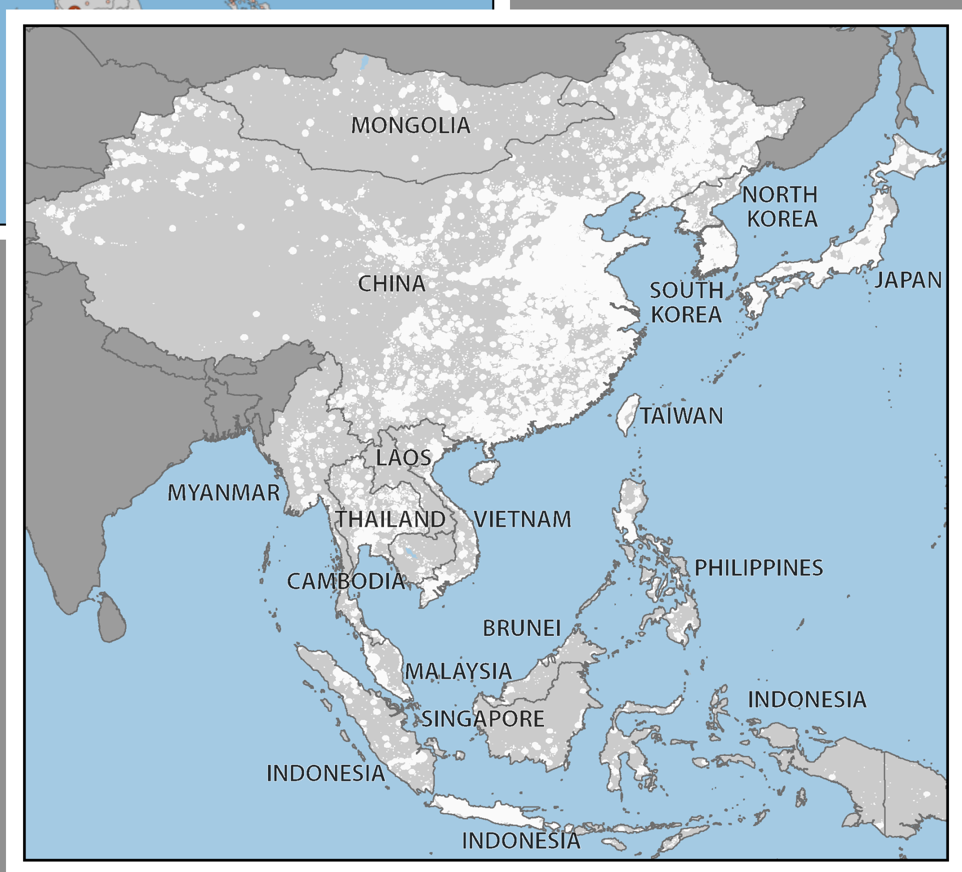
3. University of Wisconsin, Madison

Outline:

1. Mapping urban expansion globally, 2000-2010.
2. Landsat spectral mixture analysis (SMA) and Boston urban heat island.
3. Testing of project central hypothesis.

1. Mapping urban expansion globally: Methods/results for North America and East Asia, 2000-10





Methods

Step 1:

Delineate study area extent

- Merge 2001 MODIS map of urban extent with all point datasets on cities (GRUMP, UN, etc.)
- Buffer by urban patch size

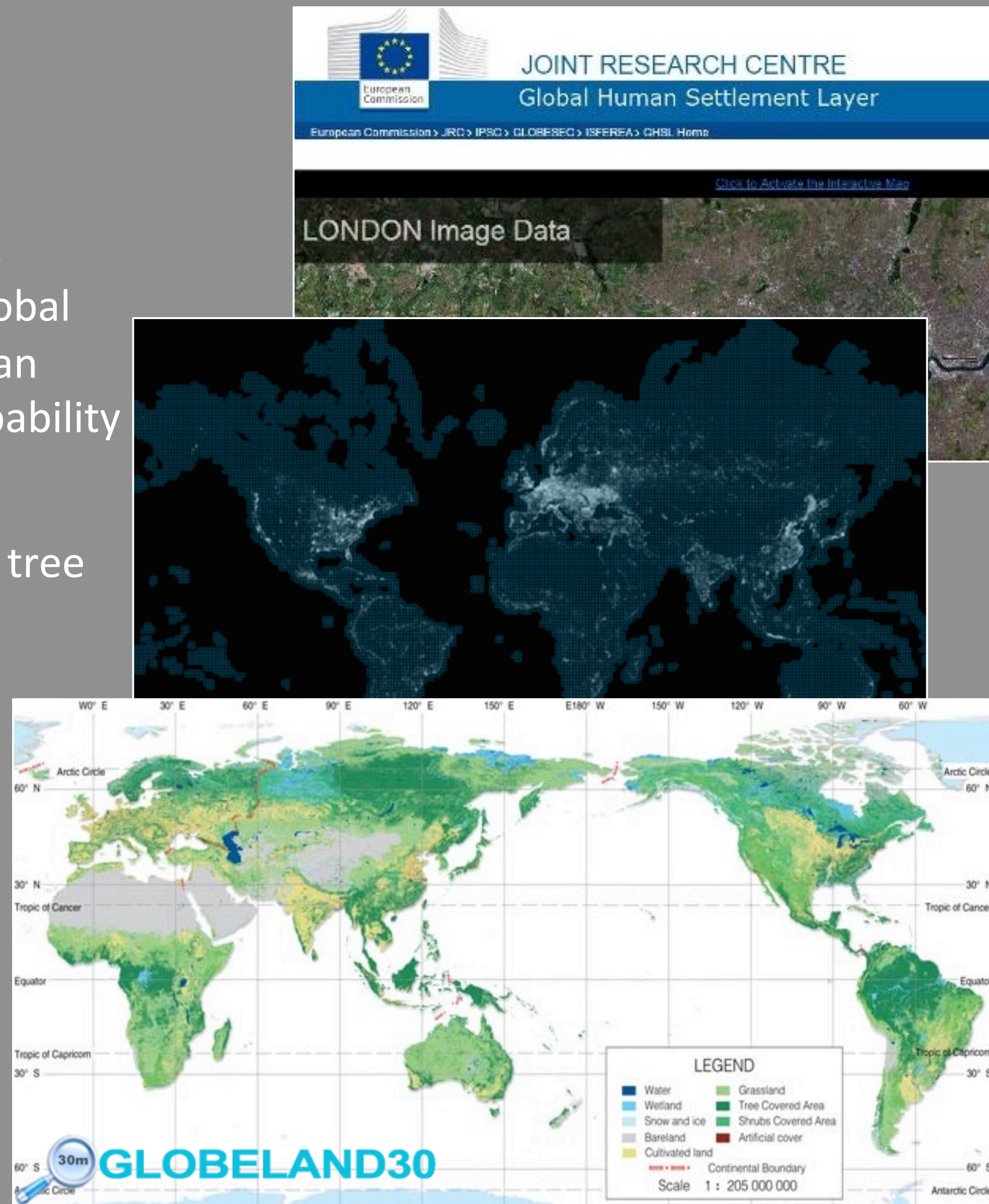
A. Schneider et al., UW

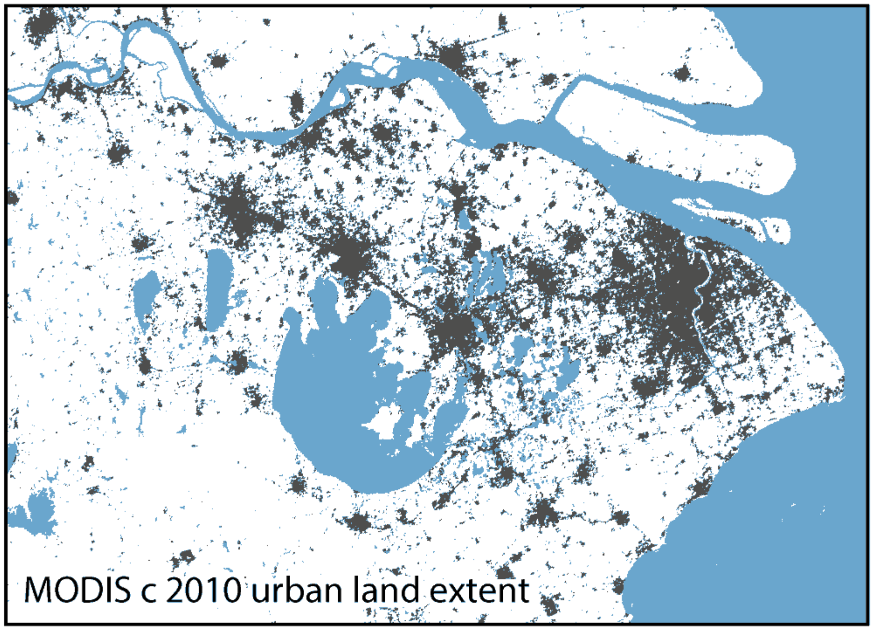
Methods

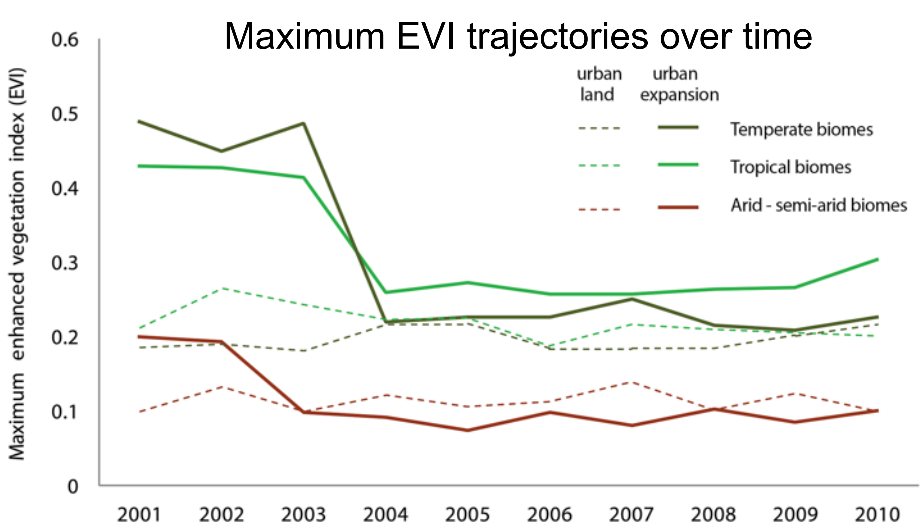
Step 2:

Characterize urban extent, c. 2010

- Synthesize new global urban maps (Landsat scale) – Globeland30, Global Human Settlement Layer, DLR urban extent map – to create urban probability surface at 500m resolution.
- Merge with MODIS 500m decision tree classification of urban land, using Bayes Rule (Mertz et al., 2015).







Methods

Step 3:

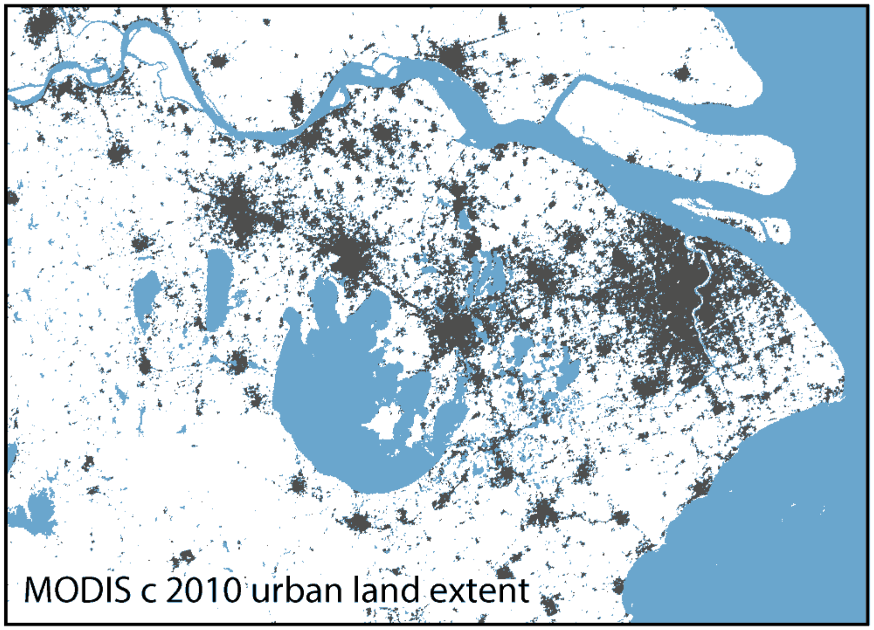
Change detection

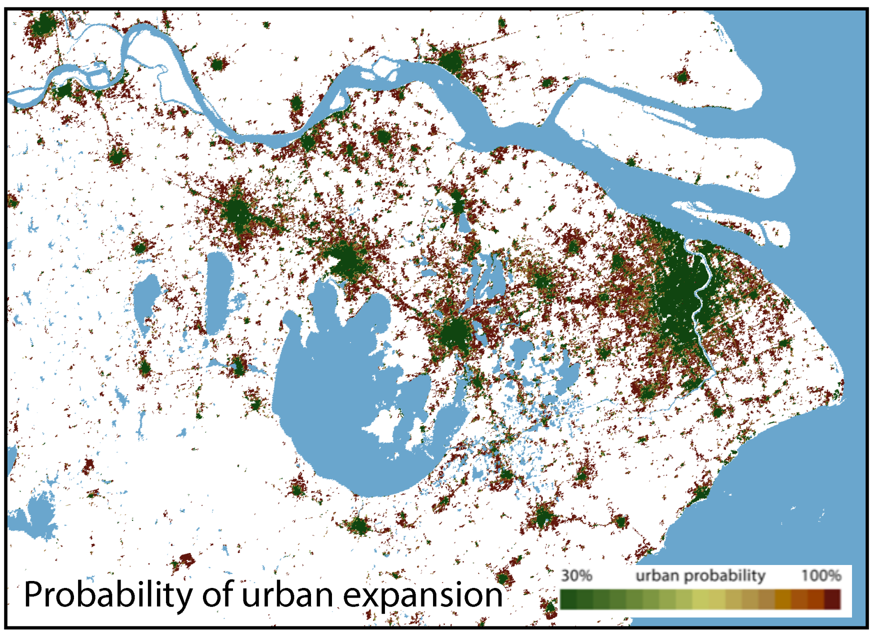
- Work backwards – were 2010 urban areas built-up in 2000, or did they become urban between 2000 and 2010?
- 10 years growing season max EVI data from MODIS (2001-2011).
- Supervised boosted decision tree algorithm
- Training data:

  (1) stable urban areas
  (2) areas that became urbanized, 2000-2010

- Output probabilities iteratively thresholded, compared to c2010 Google Earth imagery.

A. Schneider et al., UW





Schneider et al., UW

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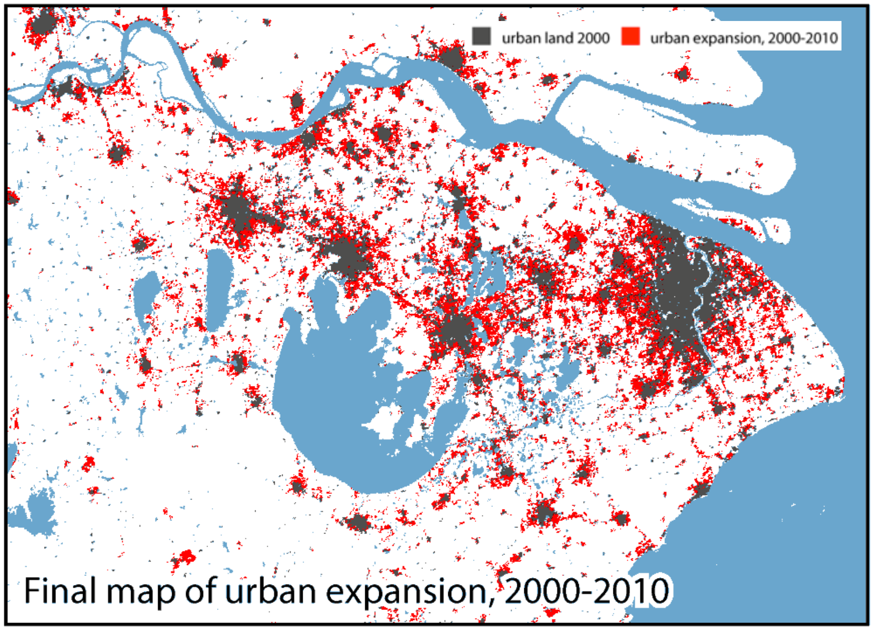

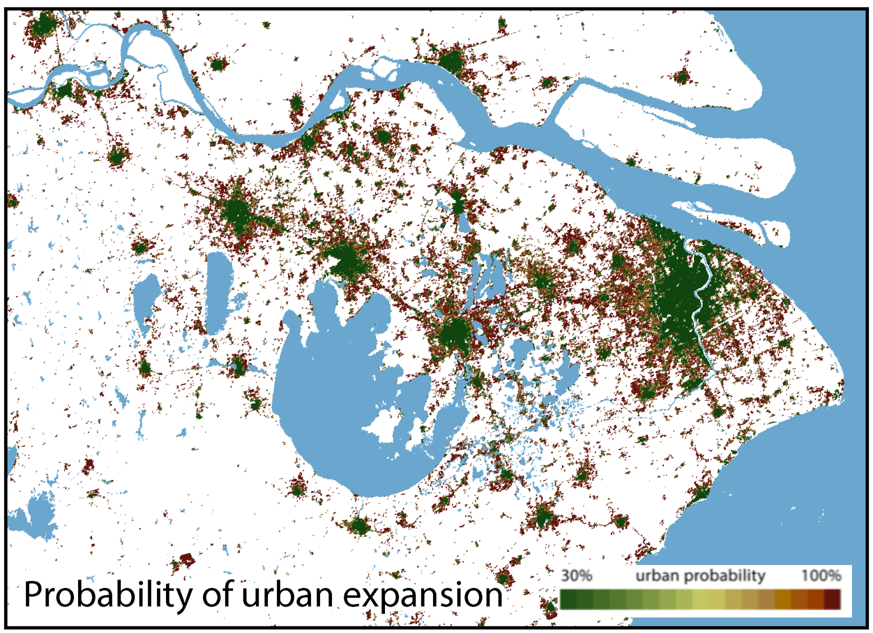

Schneider et al., UW

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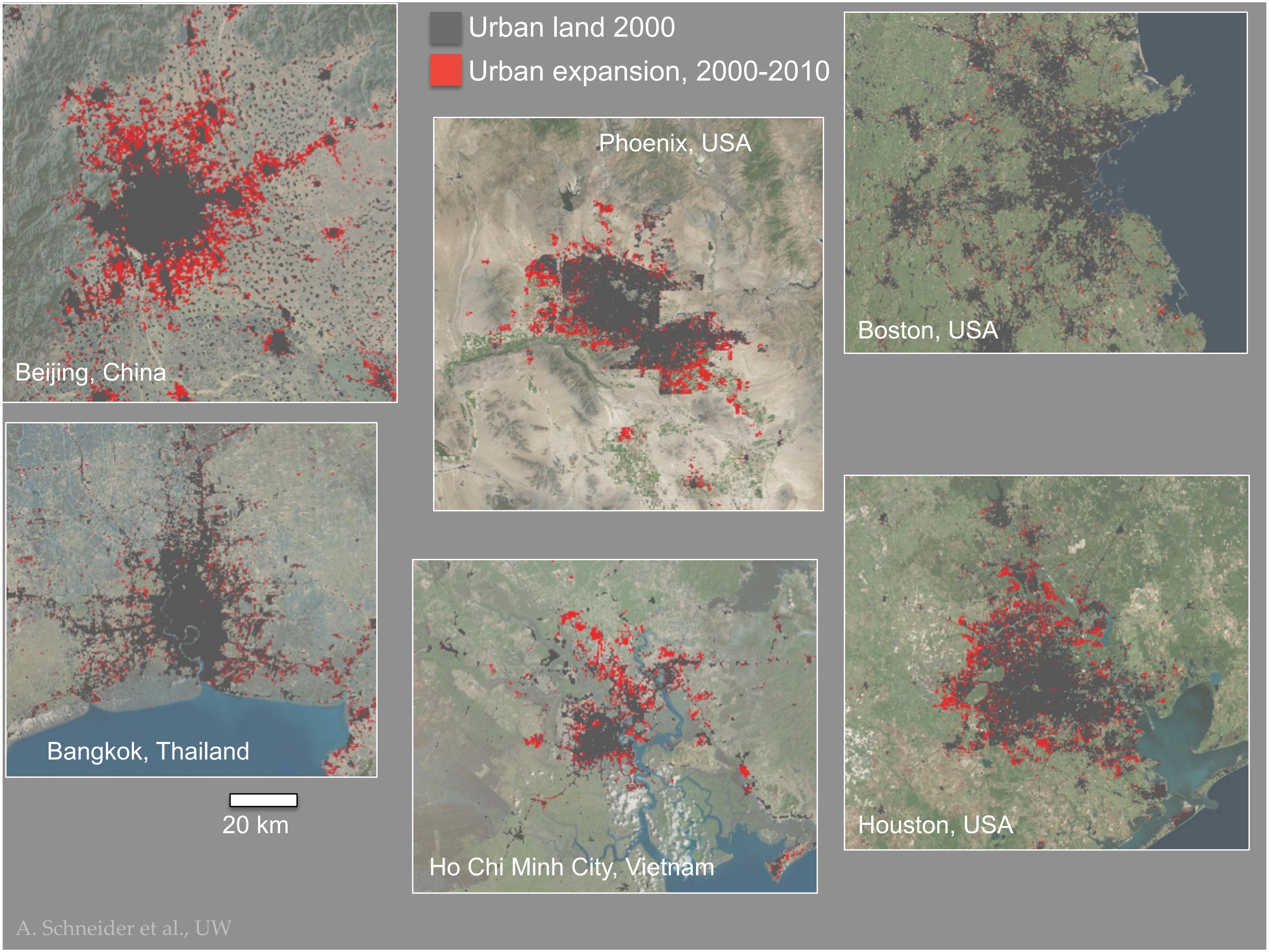
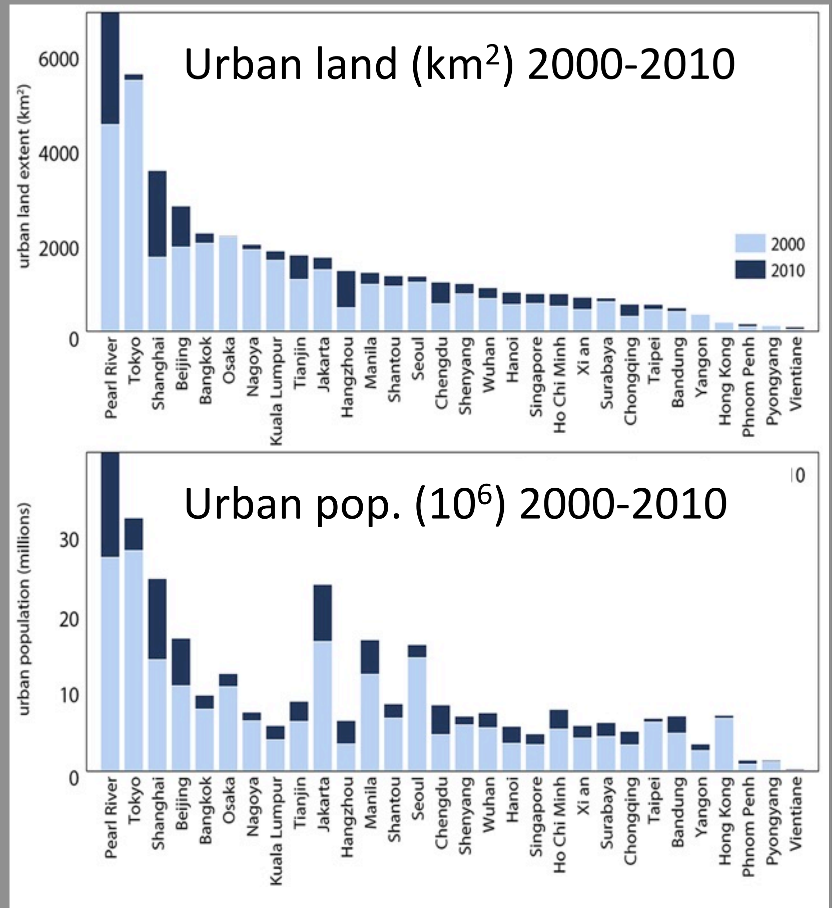

Urban land 2000
Urban expansion, 2000-2010
Beijing, China
Phoenix, USA
Boston, USA
Bangkok, Thailand
Ho Chi Minh City, Vietnam
Houston, USA
20 km
A. Schneider et al., UW

Mapping urban expansion

Progress and next steps

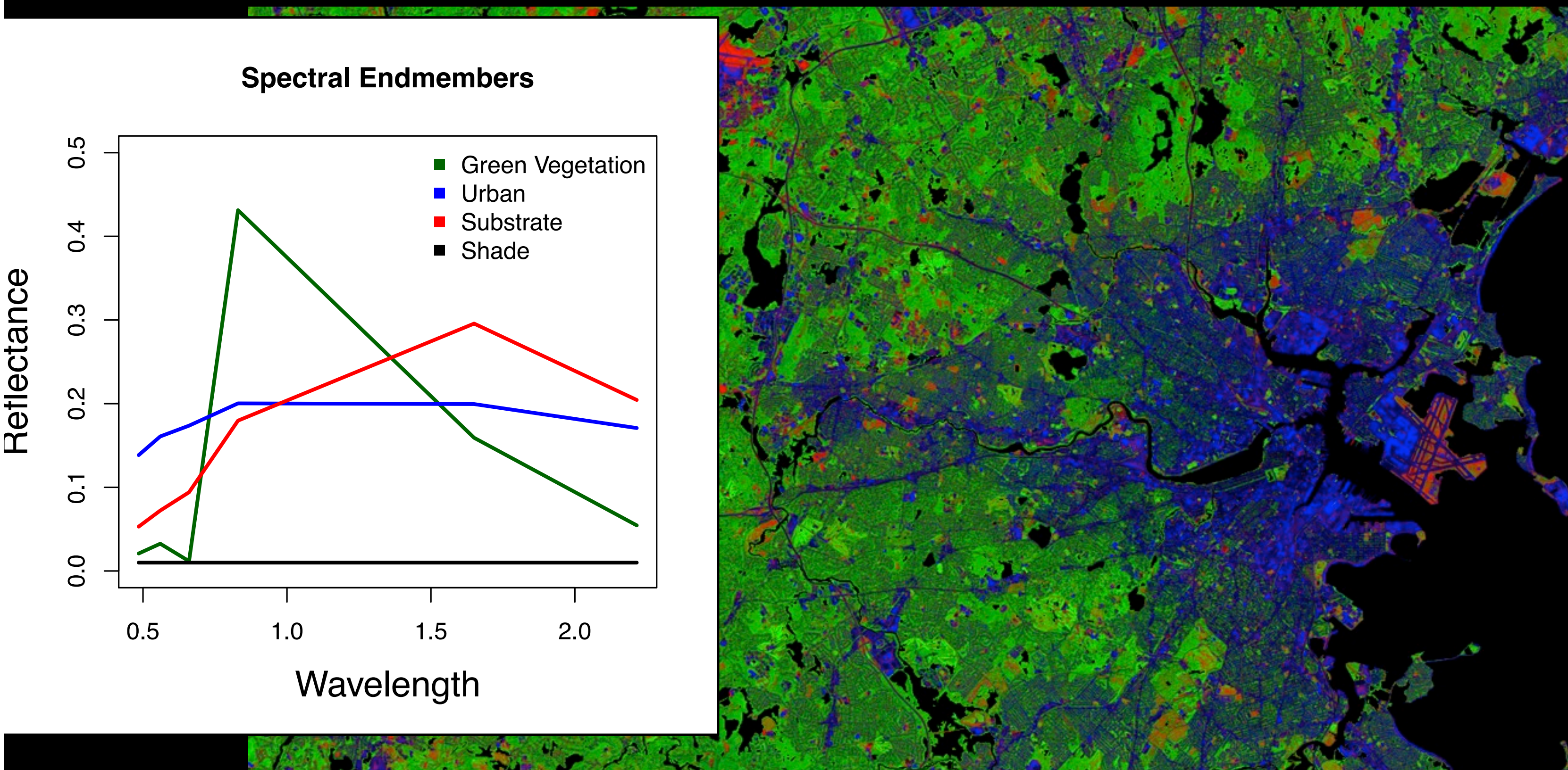
- Mapping c. 2010 global urban land extent to be completed in 2016.
- Change detection work ongoing; maps released as completed.
- Robust, two-tier accuracy assessment using stratified random sample of sites labeled by multiple analysts, double-blind procedure.

City-level results for top 30 urban agglomerations in East Asia.



A. Schneider et al., UW

2. Boston MA – Urban Heat Island Landsat Spectral Mixture Analysis



August, 2010

R: Substrate G: Green Vegetation B: Urban

4th end-member (not included): Shade

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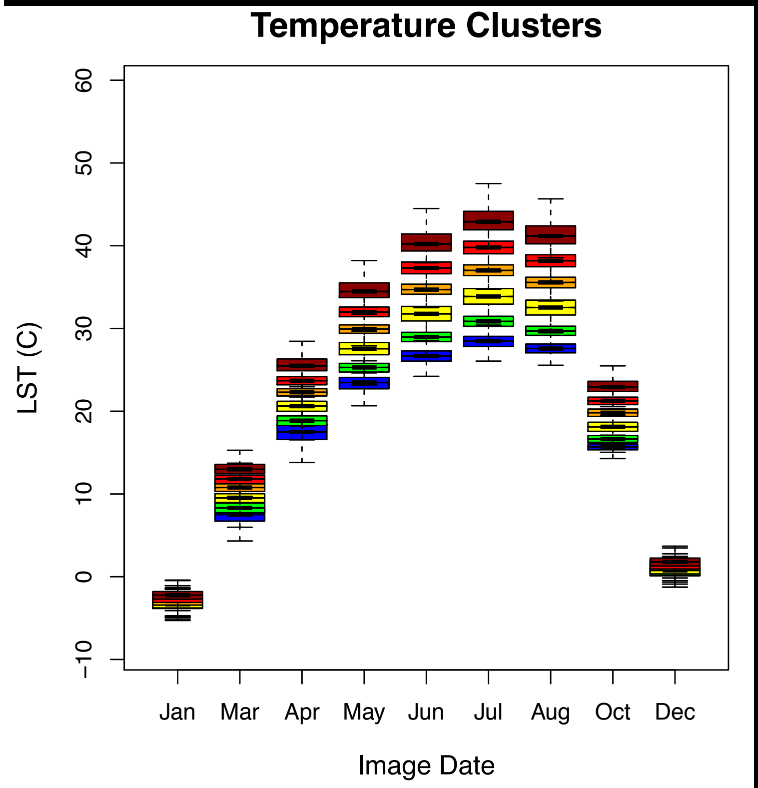
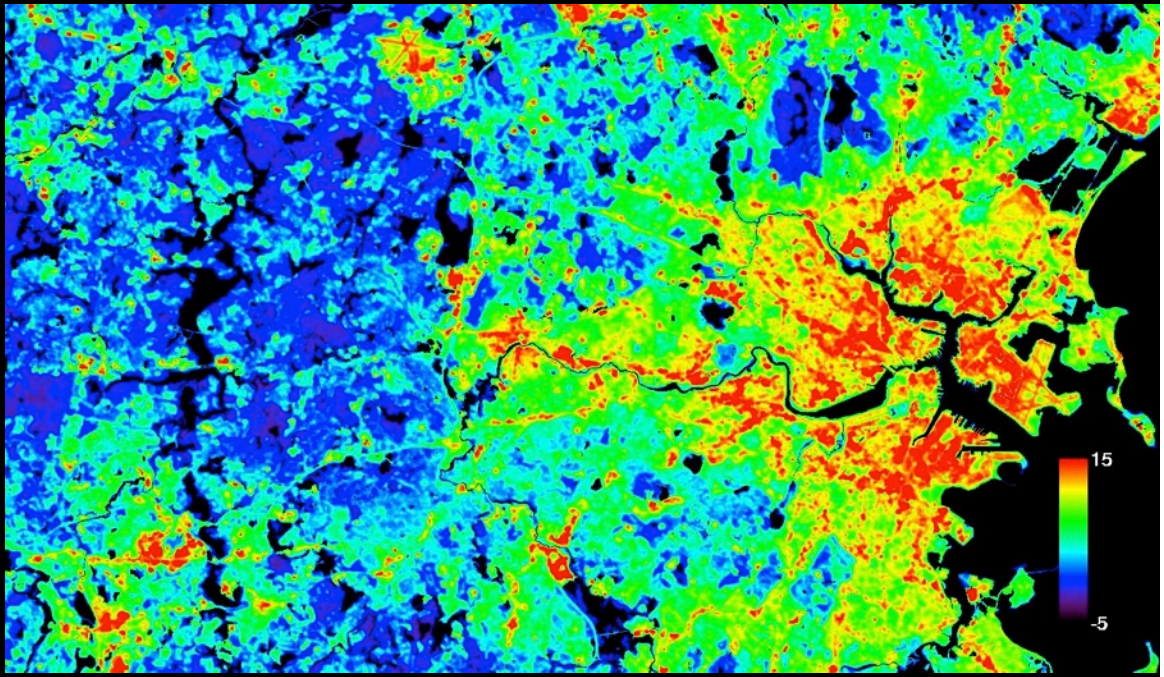
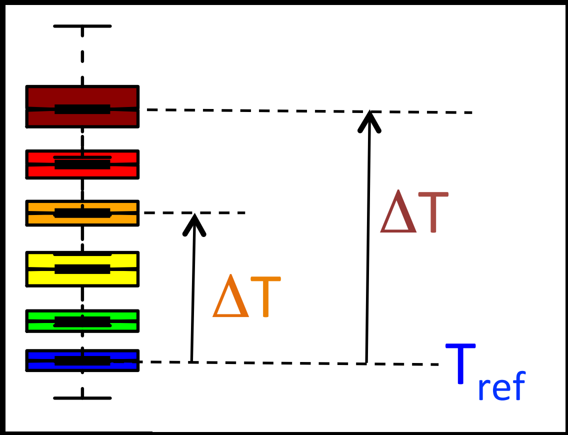
Defining Urban Heat Island: daytime ΔT

Land Surface Temperature Clusters



Urban Heat Island, August 2010





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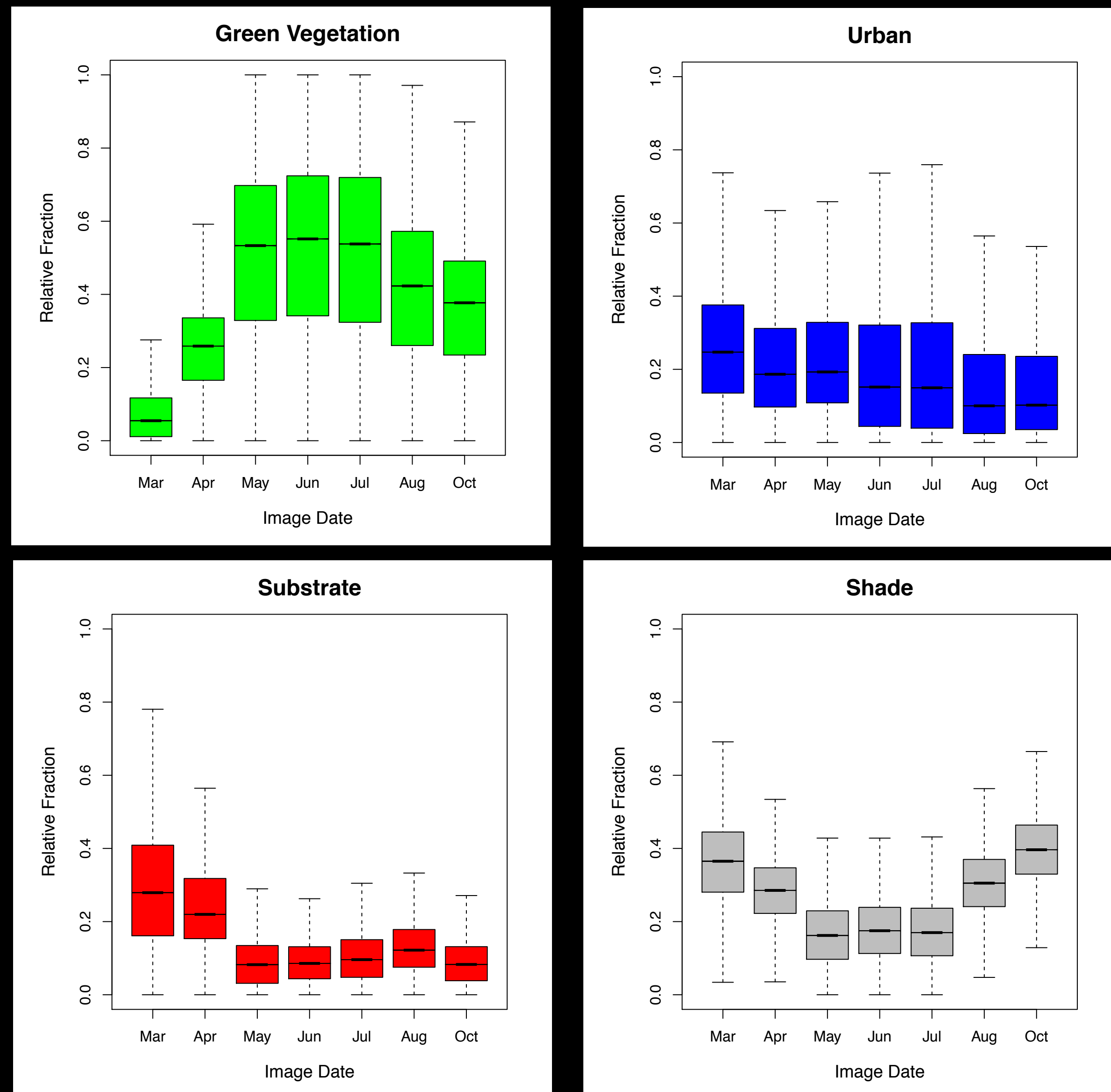
Spectral Mixture Analysis

Relative fractions of four endmembers vary across scene and through year.

1. ***green vegetation***,
2. ***urban*** (built),
3. ***substrate*** (e.g., dirt, dead grass & leaves, leafless trees),
4. ***shade*** (dark).



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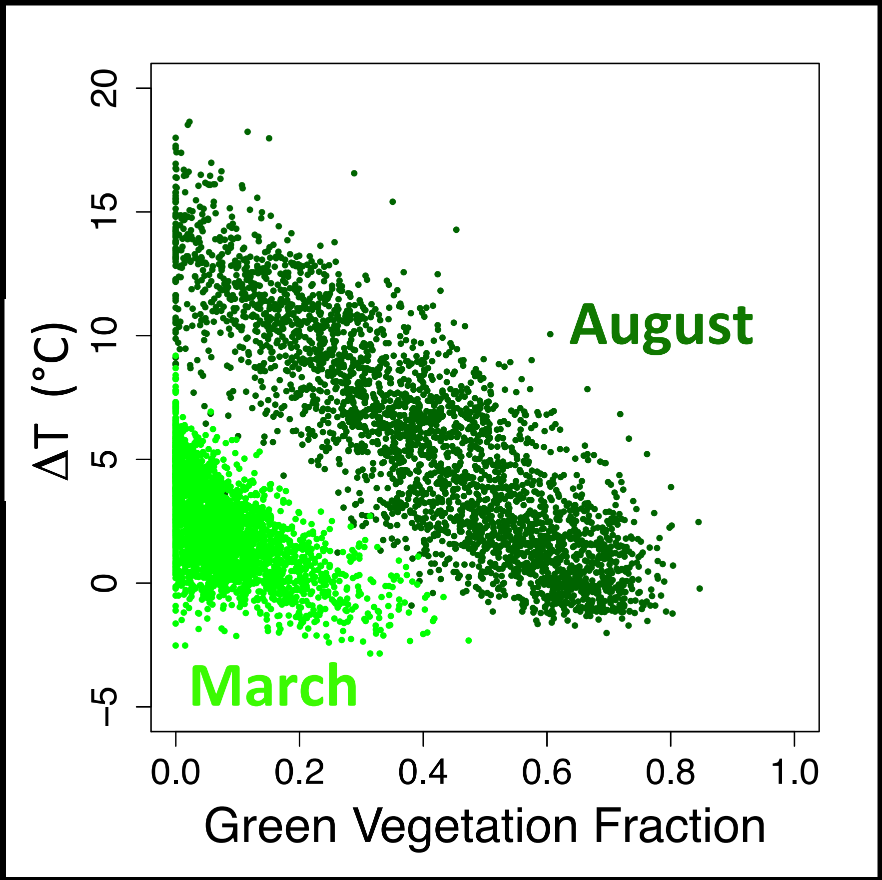
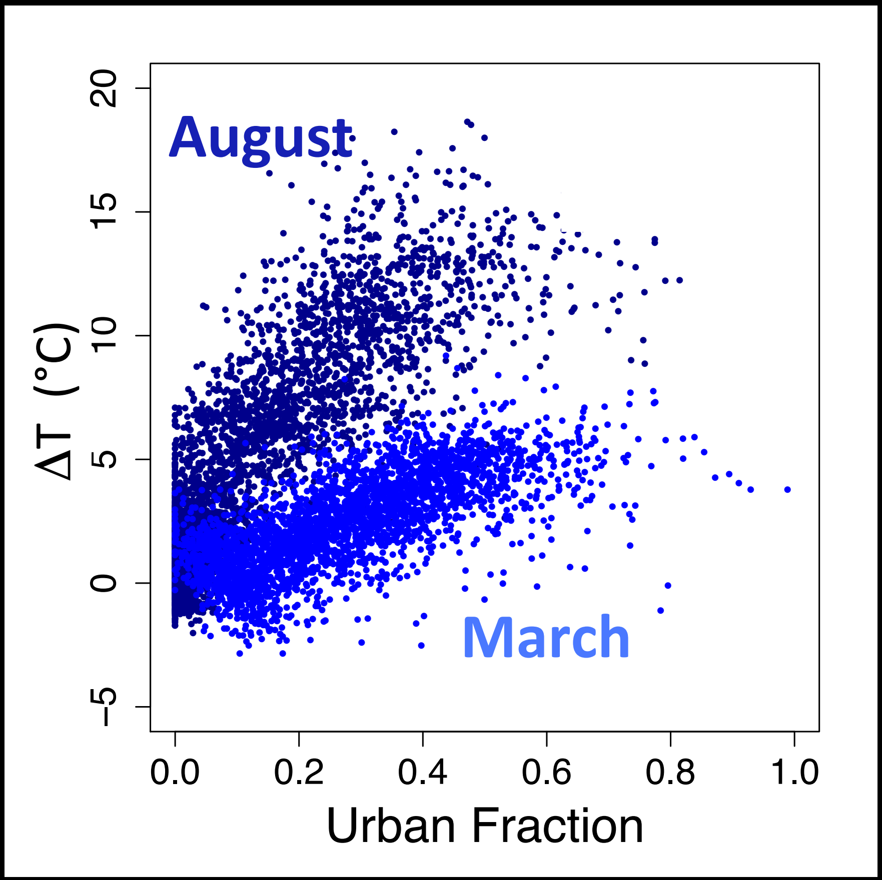
Urban Heat Island ~ Spectral Mixture Analysis

ΔT increases in summer and with urban fraction;
ΔT decreases with green vegetation fraction.





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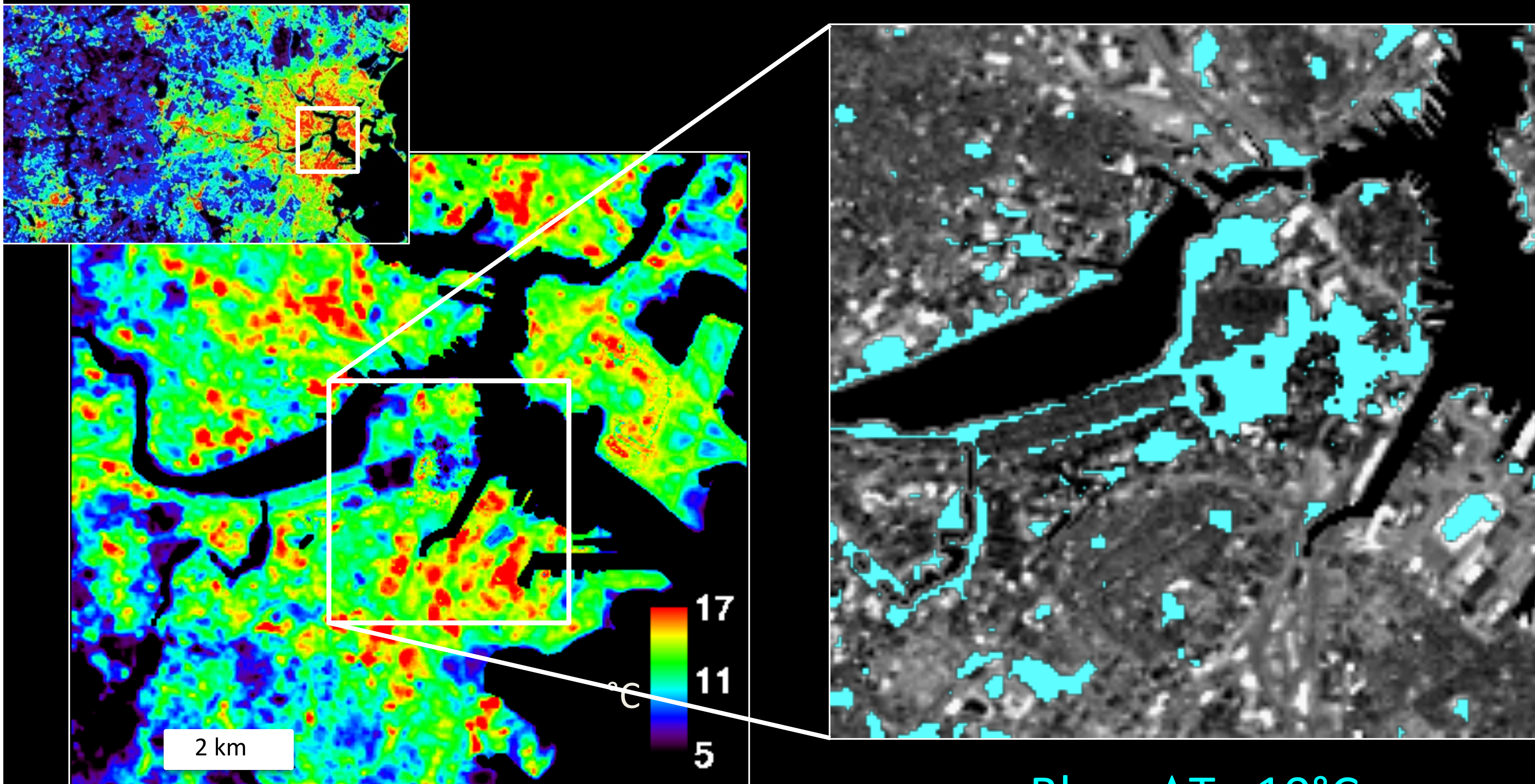
Urban Heat Island

ΔT high in downtown Boston, but there are cooler spaces.



Blue: ΔT <10°C

Urban Heat Island

August, 2010

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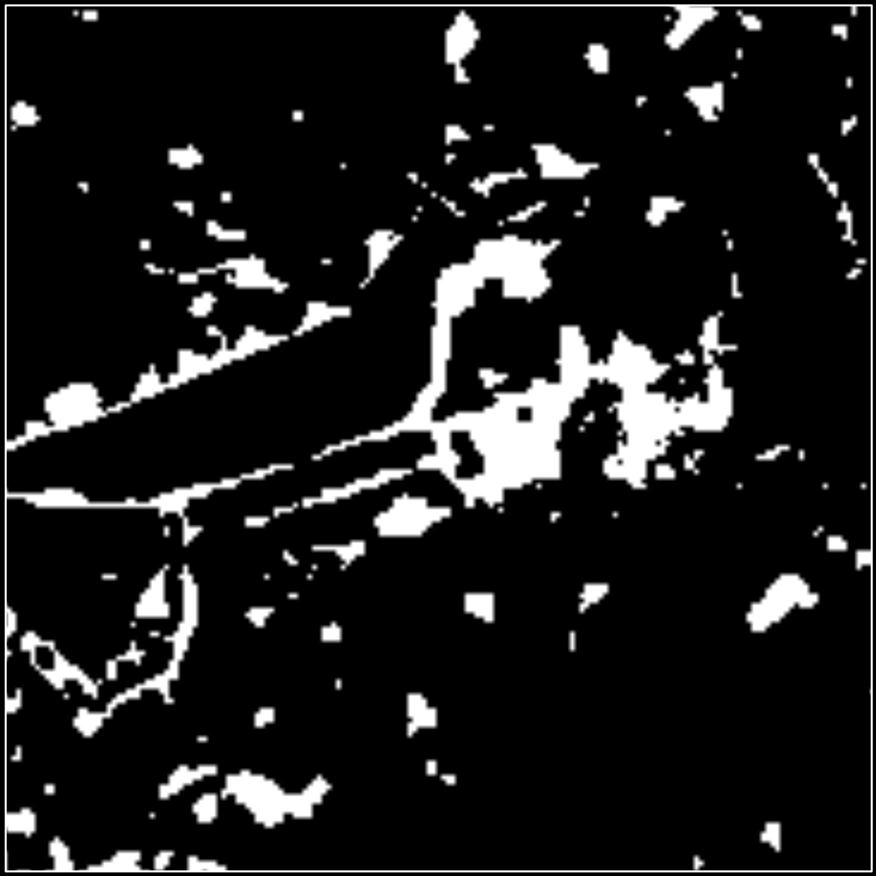
Urban Cool Islands



Low ΔT

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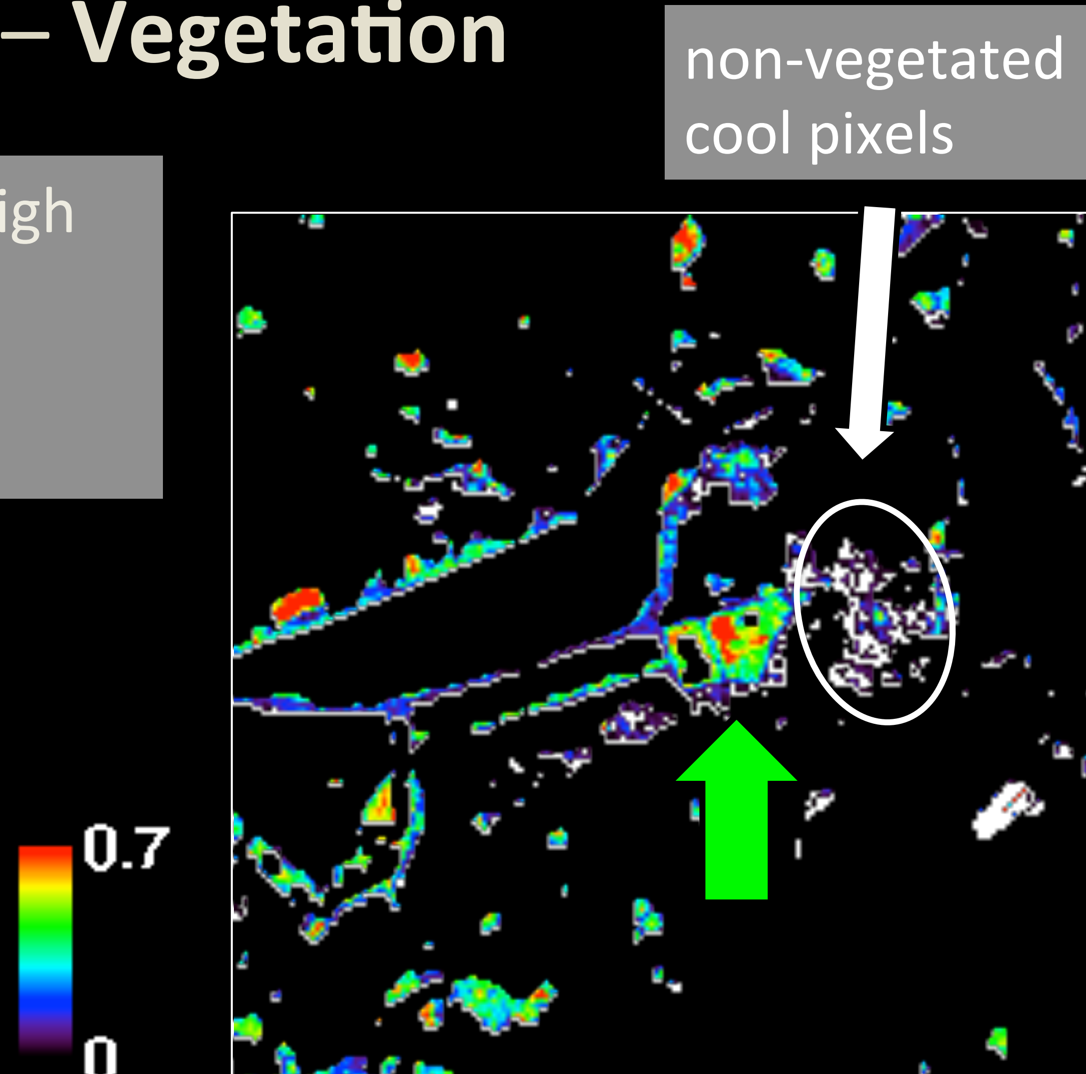
Urban Cool Islands – **Vegetation**

Green/**Red**: Low ΔT with high green vegetation.
White: low ΔT with 0% vegetation.



Vegetation fraction

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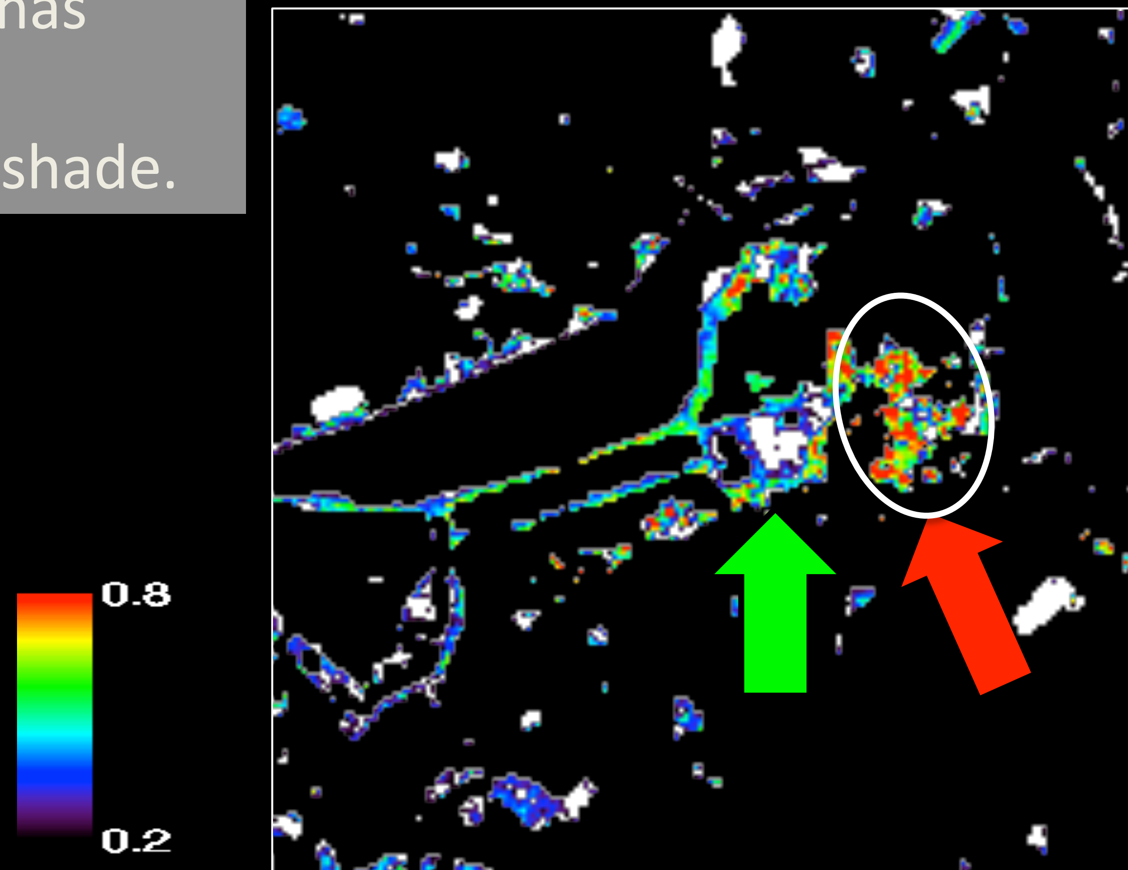
Urban Cool Islands – **Shade**

Red/**Orange**: low ΔT that has abundant shade.
White: low ΔT with <20% shade.

Shade fraction



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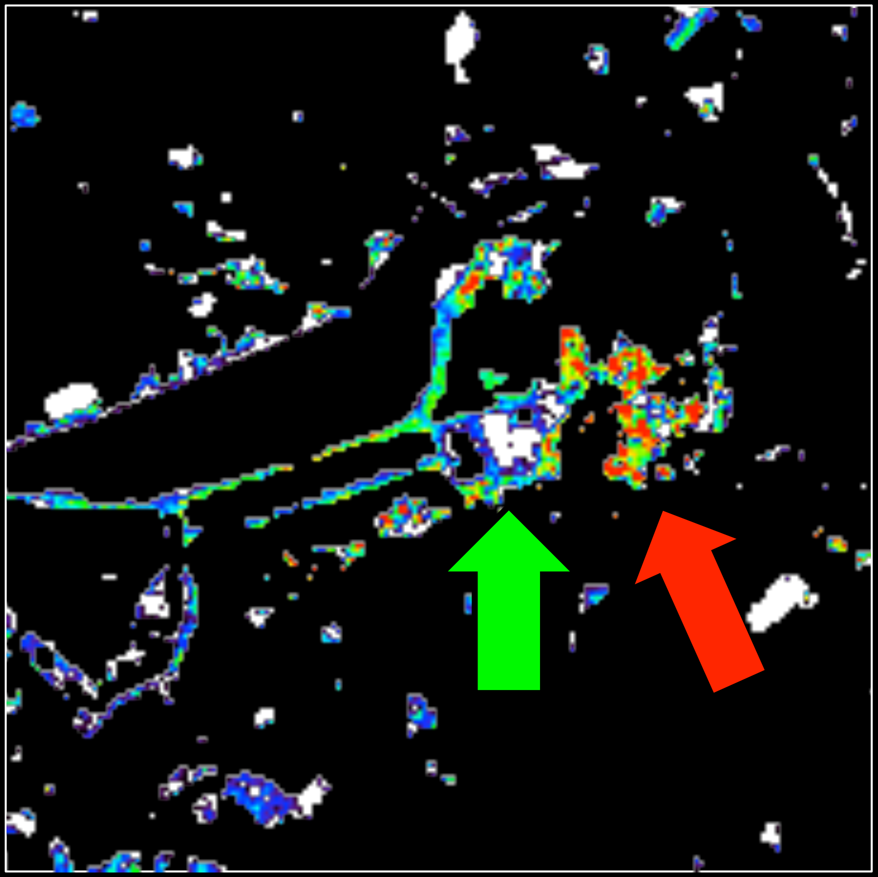

Urban cool islands: Boston's urban core includes cooler areas arising not only from vegetation, but also from shading.

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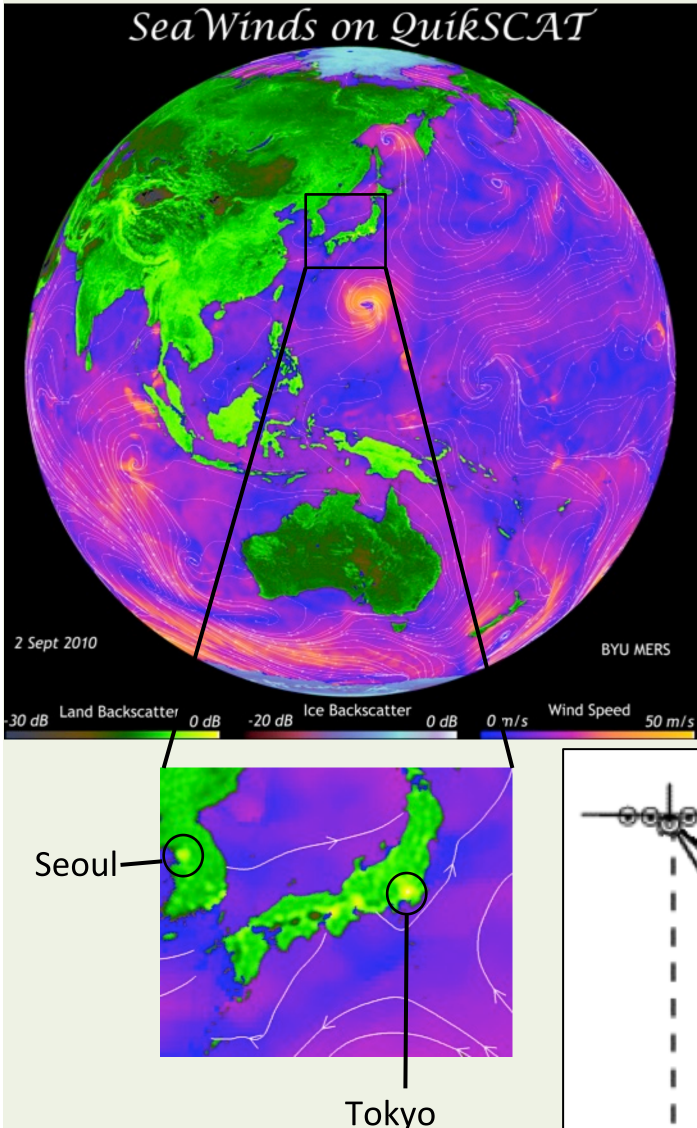
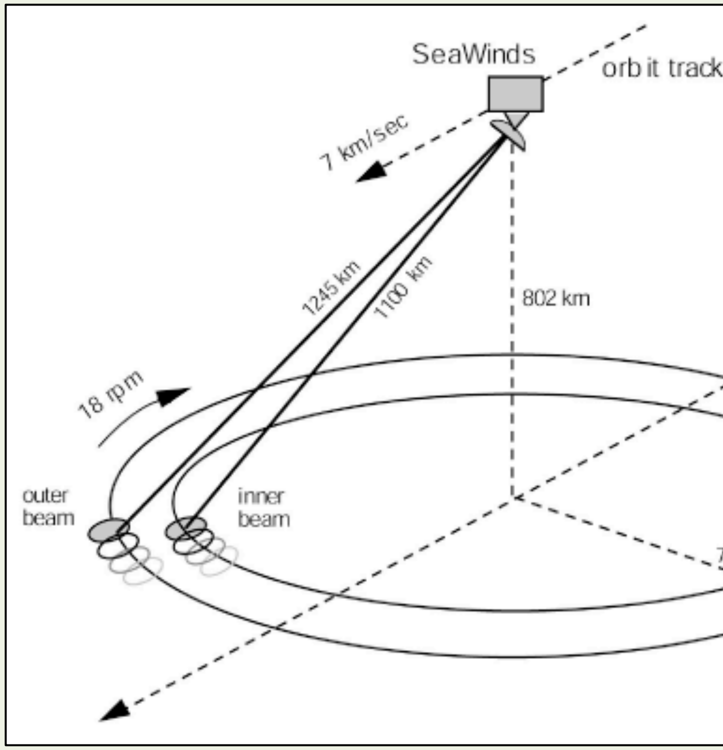
3. Hypothesis – Urban core development impacts urban heat island

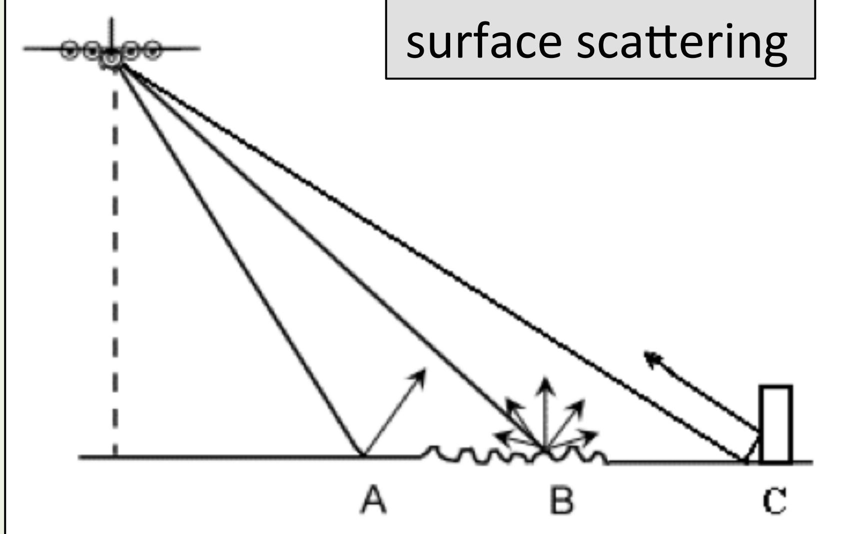




Ku-band microwave scatterometer

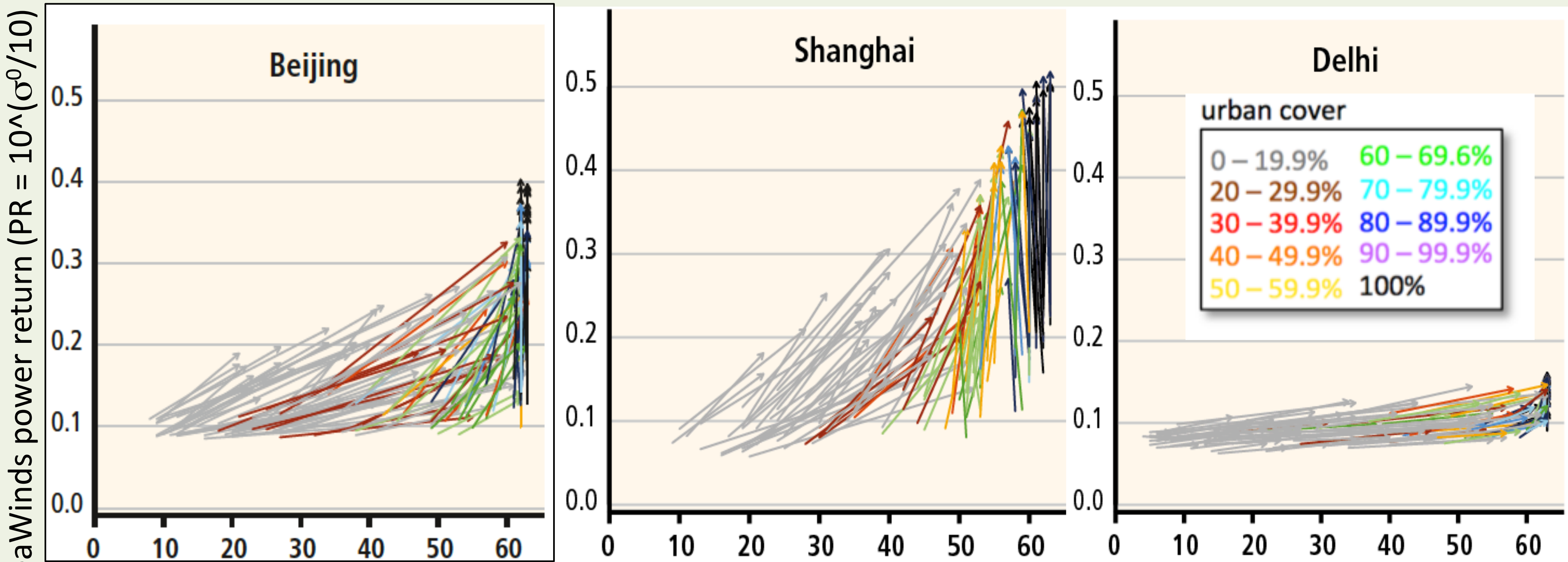
Big cities have strong backscatter.

surface scattering



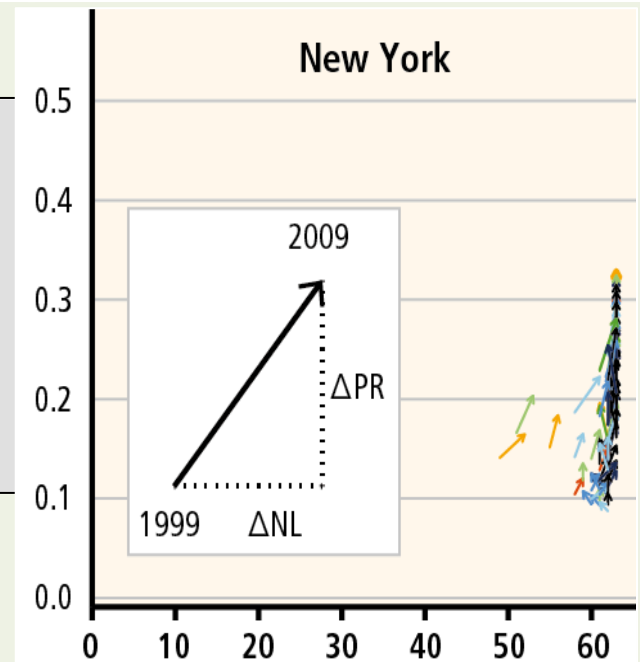
A – specular reflection
B – diffuse scattering
C – corner reflector

1999-2009 change in night time lights and microwave backscatter



DMSP/OLS night time lights (NL; max. = 63)

- 11 x 11 grid (0.05°) centered on each city.
- summer mean backscatter; annual mean night time lights.
- arrows point from NL and PR in 1999 to NL and PR in 2009.
- urban fraction (arrow color) from MODIS land cover product.
- water grid cells masked out.



Frolking et al. 2013 *ERL*

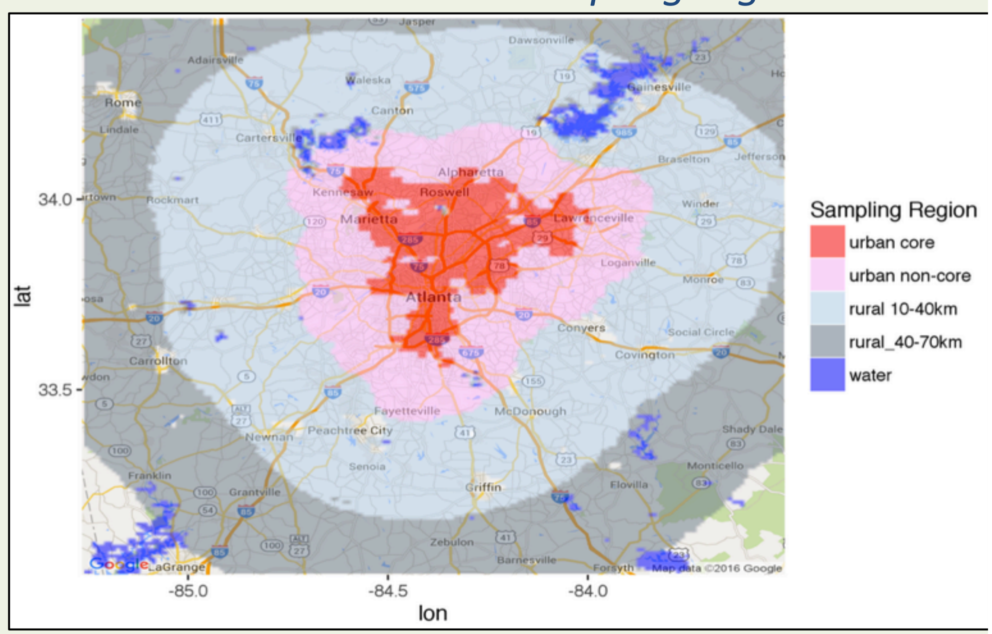
A central hypothesis of the project:
rapid growth in the urban core built environment (as quantified by Quikscat) will have an observable impact on the urban core temperature relative to surrounding rural areas that are not experiencing rapid building growth, and thus on the urban heat island.

Method:

1. Target large cities – 30 in East Asia (rapid growth) and North America (slower growth).
2. Dissaggregate into urban core, urban non-core, near rural (10-40 km), far rural (40-70 km).
3. Assemble data, including:
   - MODIS AQUA & TERRA LST (day & night);
   - MODIS EVI
   - Quikscat;
   - DMSP/OLS stable lights.

4. Evaluate UHI and trends across samples.

Atlanta urban-rural sampling regions



Seasonal time series data

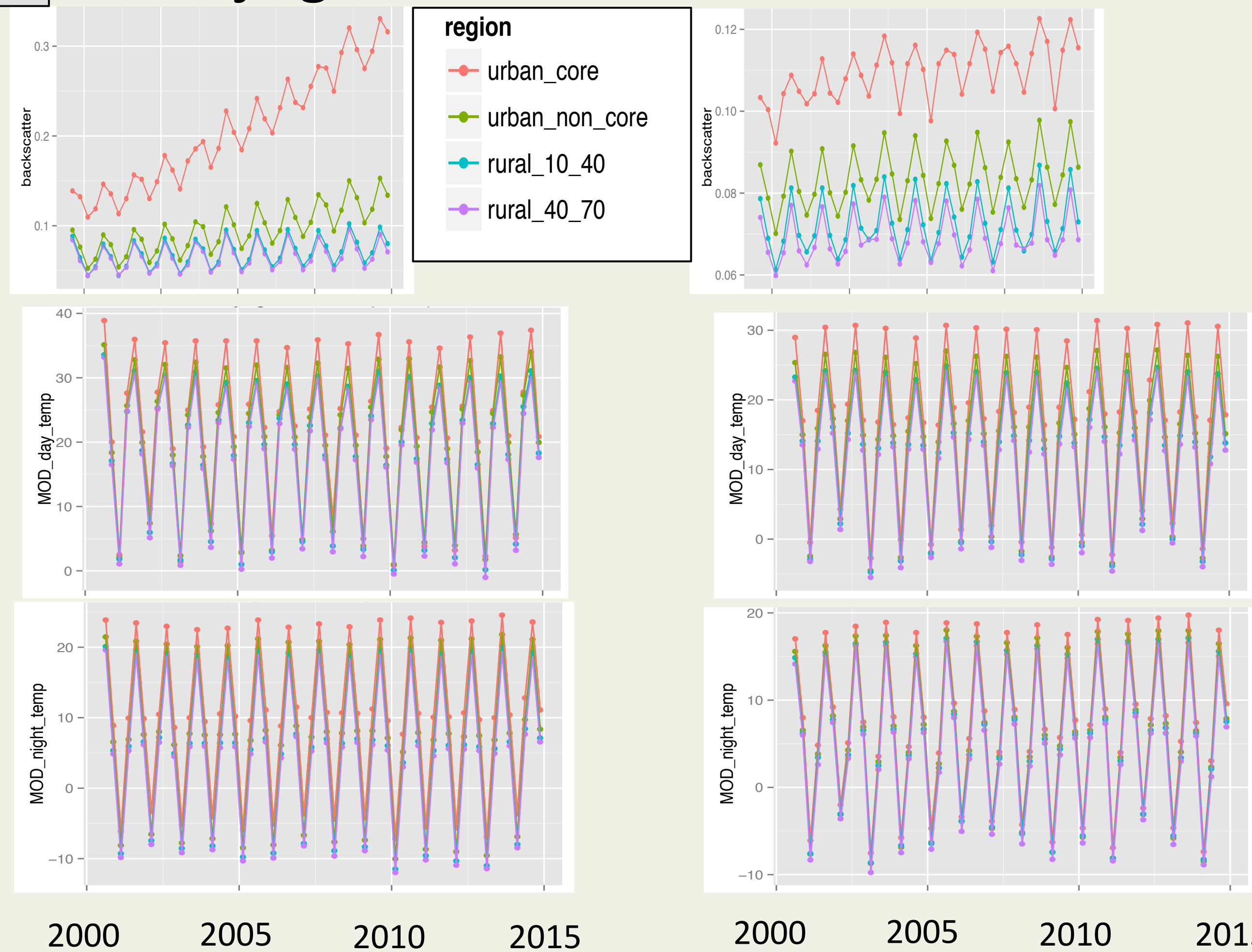
Beijing

Boston

Quikscat backscatter

MODIS Terra Daytime - LST

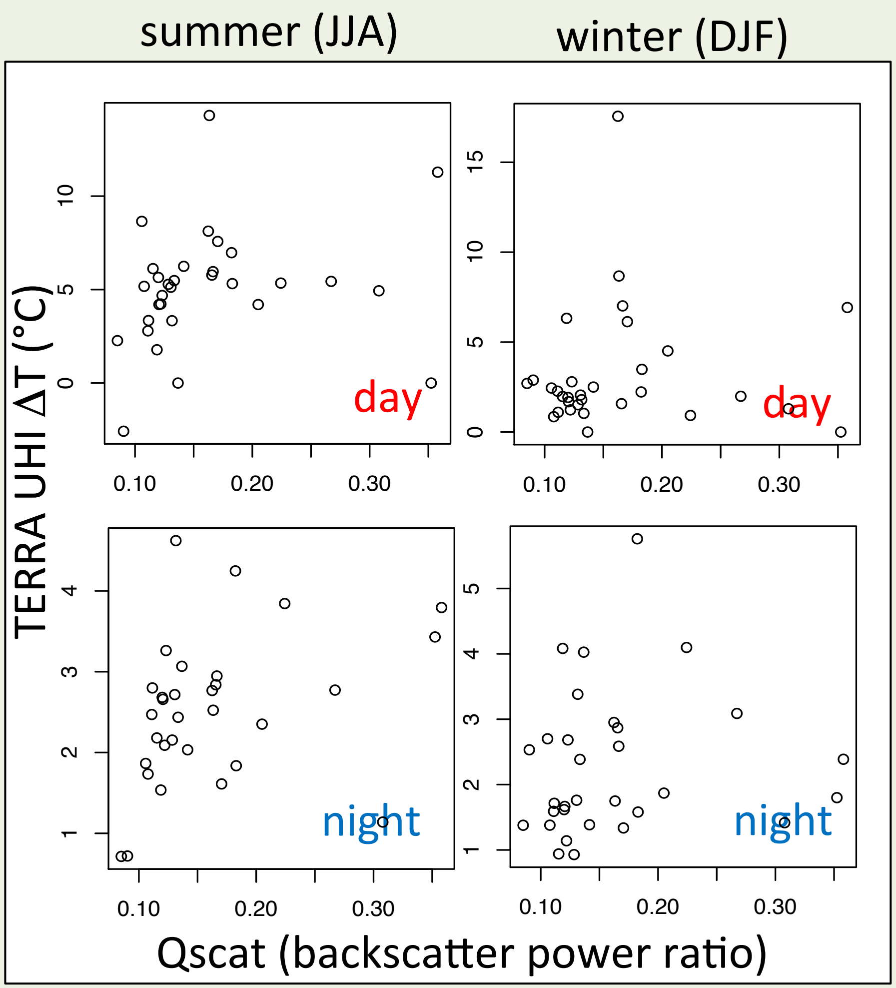
MODIS Terra Nighttime - LST



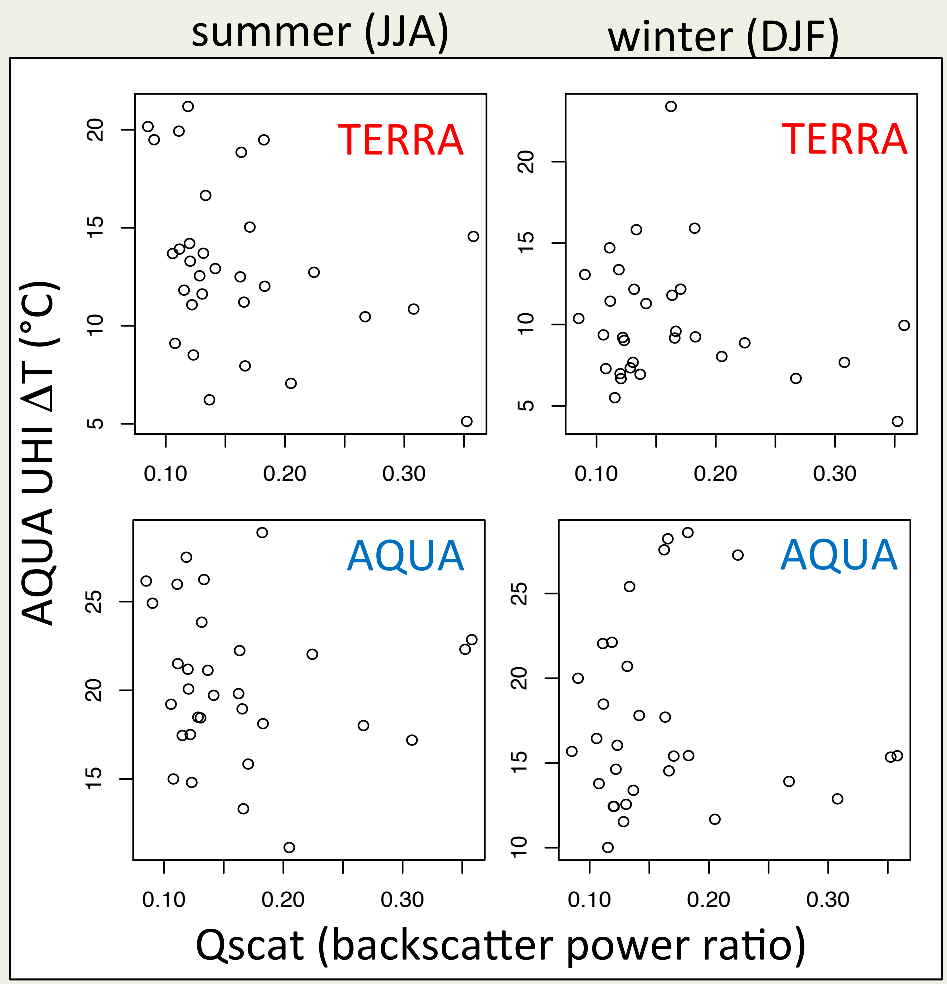
Hypothesis (trend in Quikscat → trend in LST) not supported.

30 large cities in East/SouthEast Asia and North America

Mean urban core backscatter vs mean TERRA UHI ΔT urban core minus rural 10-40 km



Seasonal mean, 2000-09, urban core diurnal LST range (day minus night)



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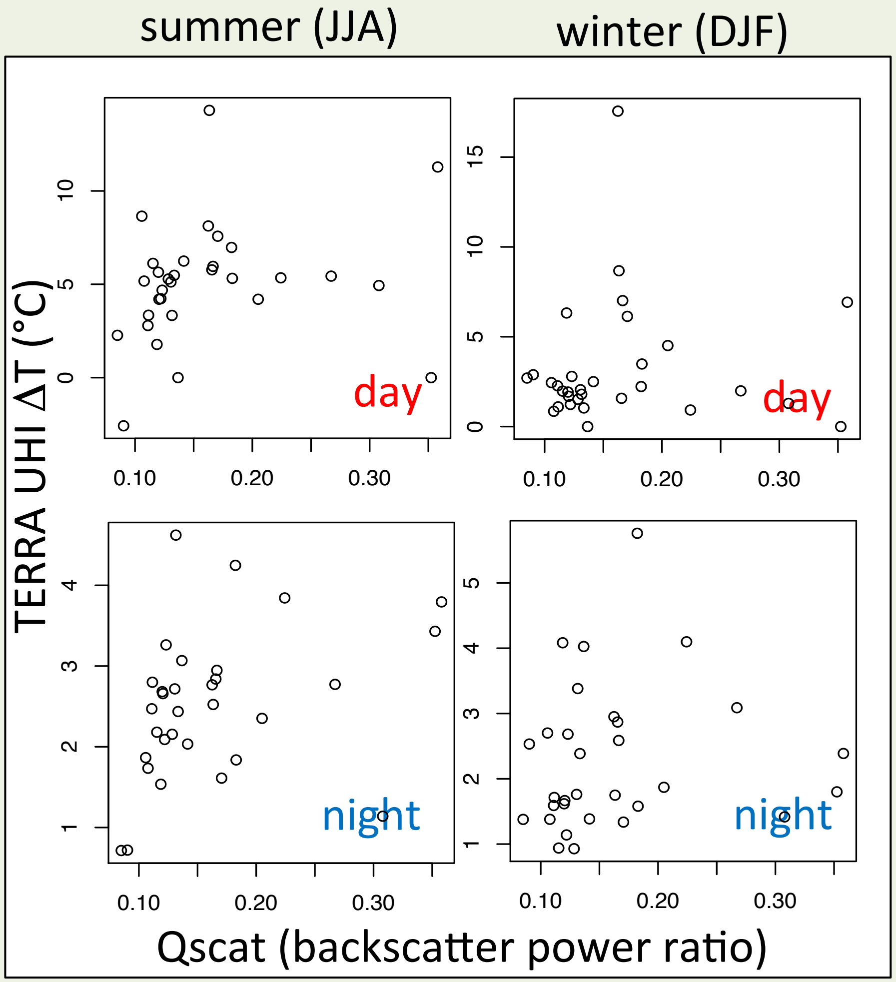
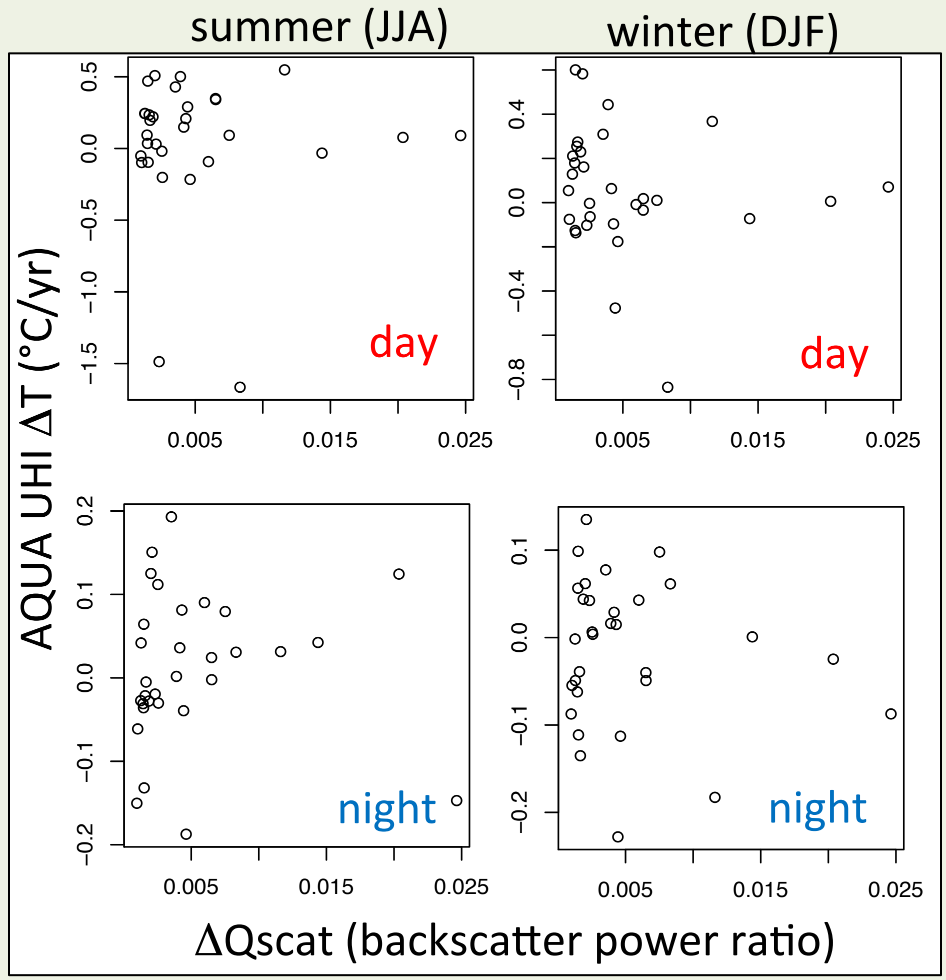


Rate of backscatter increase, 2000-09, vs rate of increase in AQUA LST UHI ΔT, urban core minus rural 10-40 km



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LETTER

doi:10.1038/nature13462

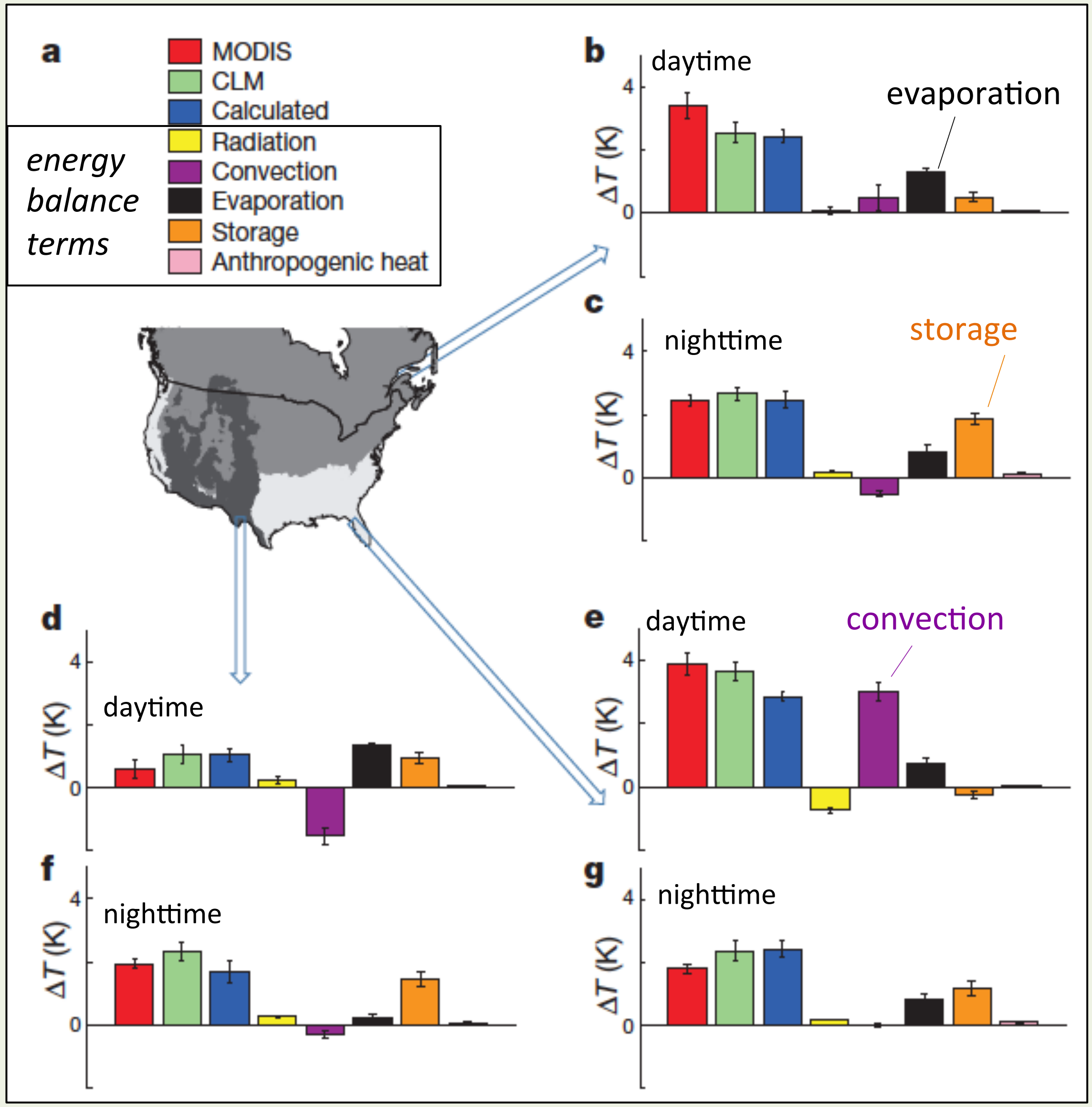
Strong contributions of local background climate to urban heat islands

Lei Zhao[1,2], Xuhui Lee[1,2], Ronald B. Smith[3] & Keith Oleson[4]

Nature, 2014

CLM dominant terms in simulated UHI:

- *evaporation* – daytime > nighttime.
- *thermal storage* – nighttime > daytime.
- *convection* – mixed geographic results.



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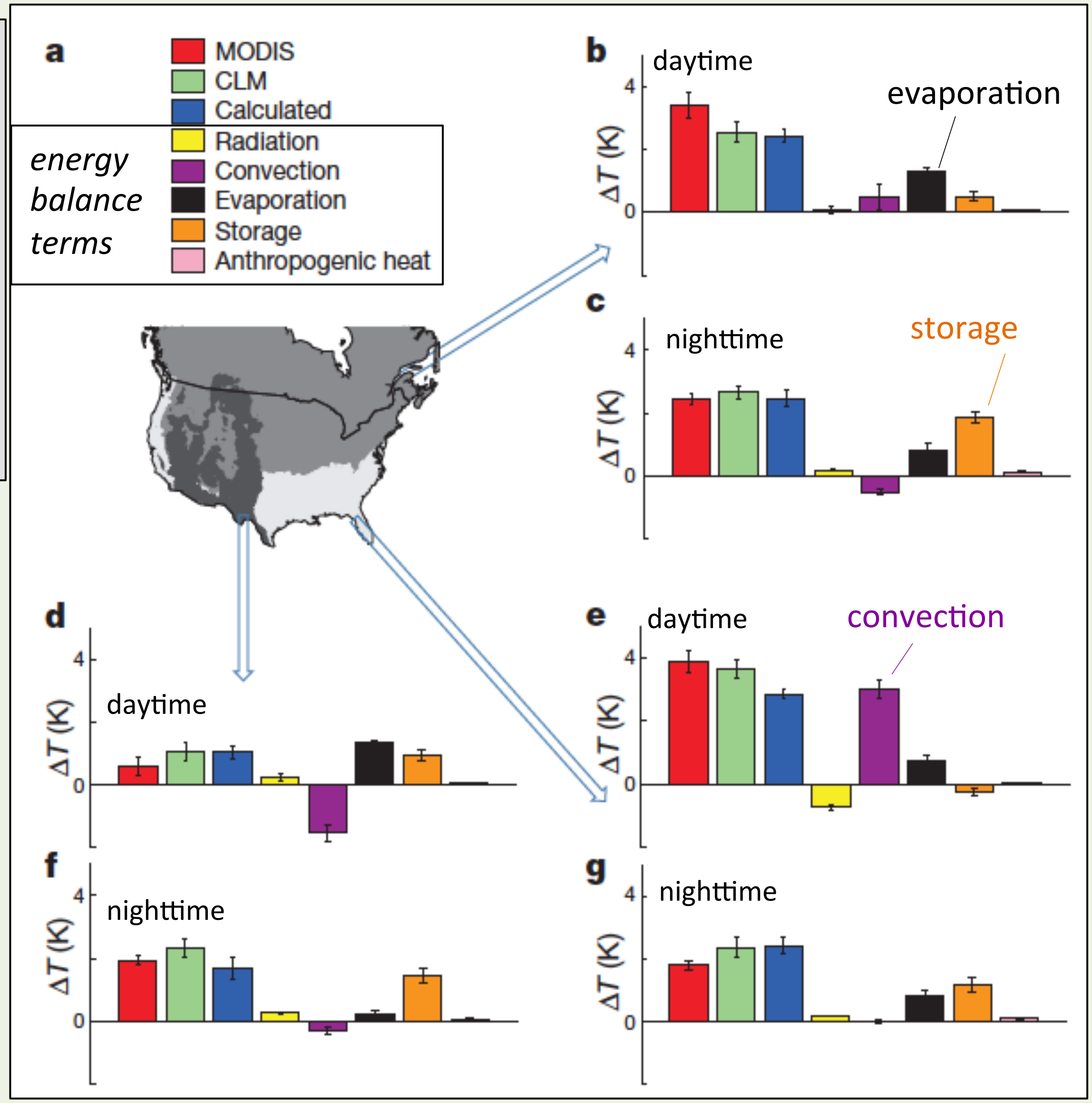

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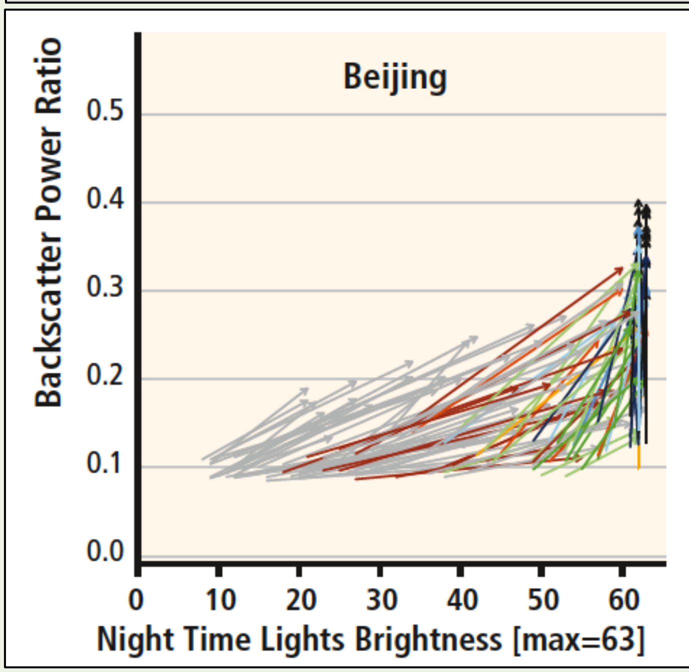
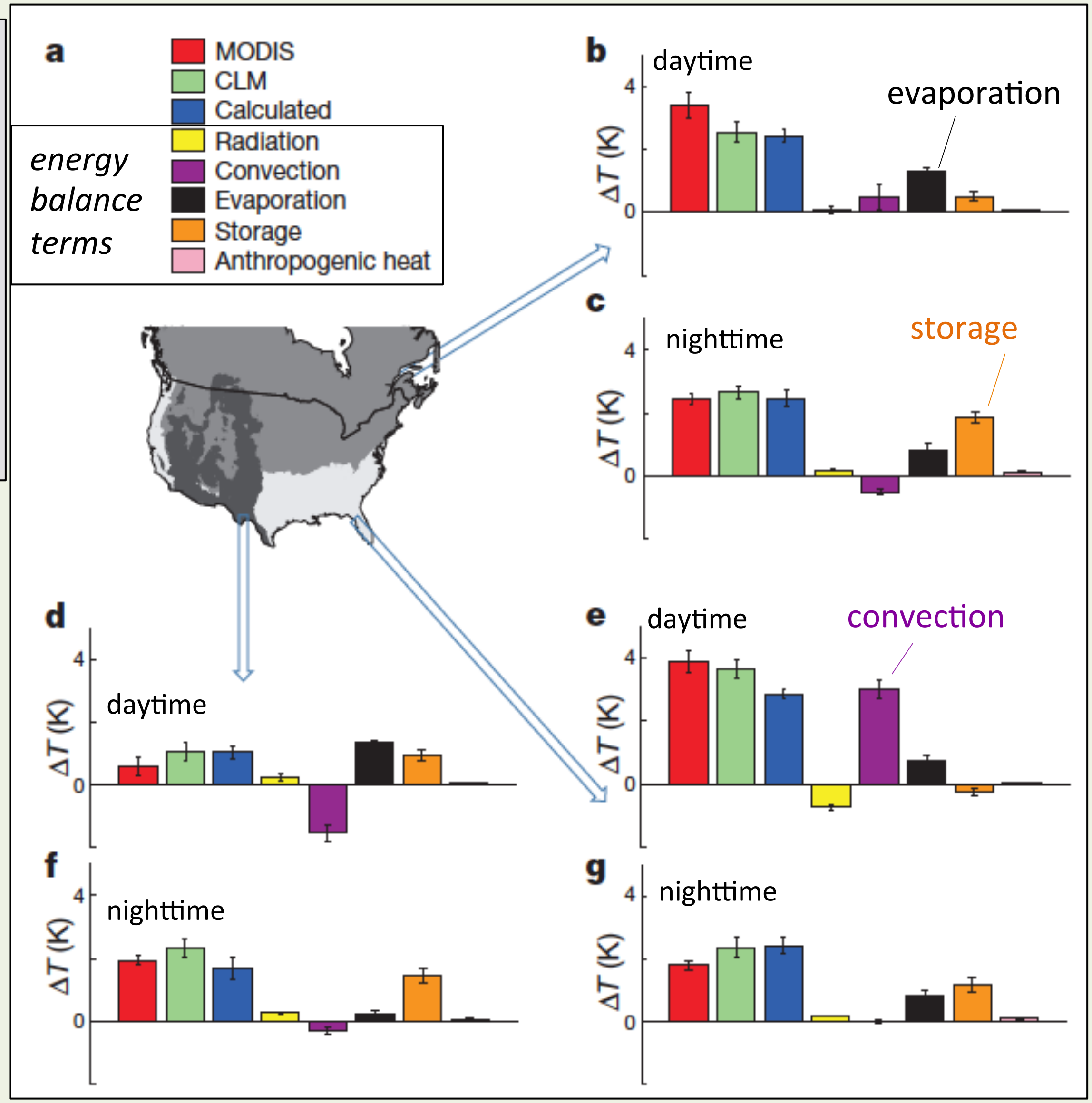
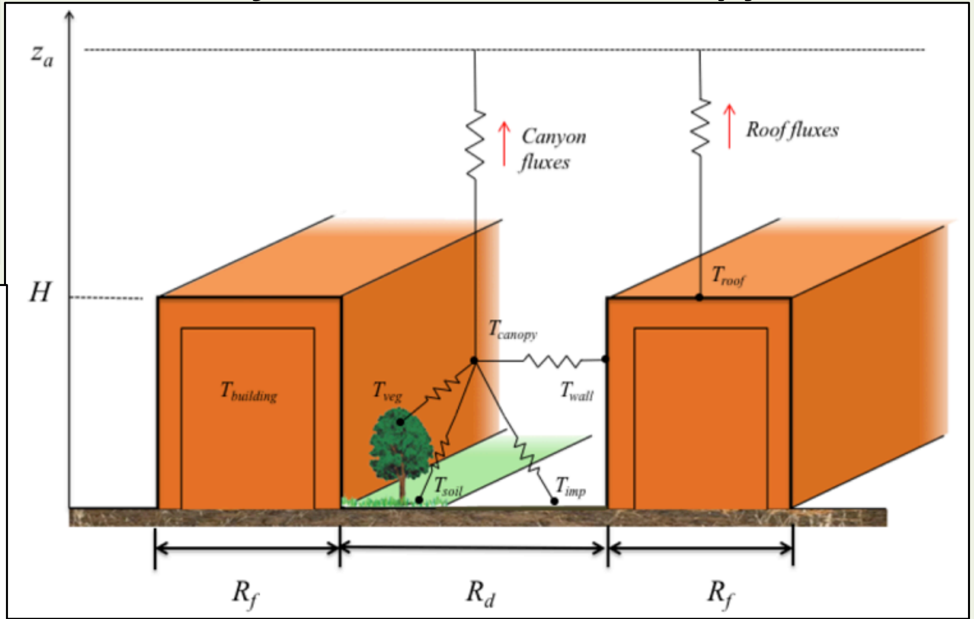




We will work with Dan Li, urban climate modeler at BU, on sensitivity of urban climate to building boom in Beijing.

Schematic of GFDL LM3 urban canopy model.



Li, et al. 2016. *J Adv Model Earth Sys*

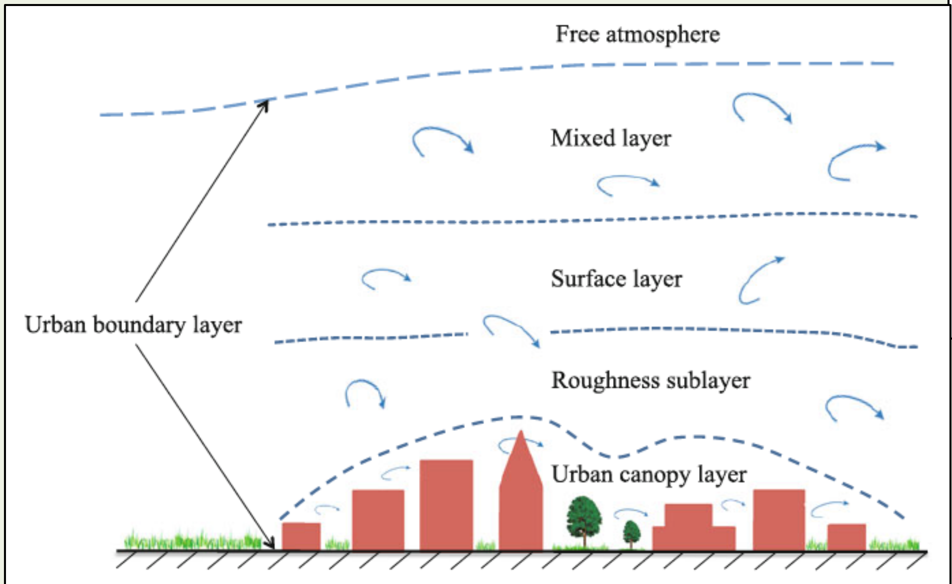
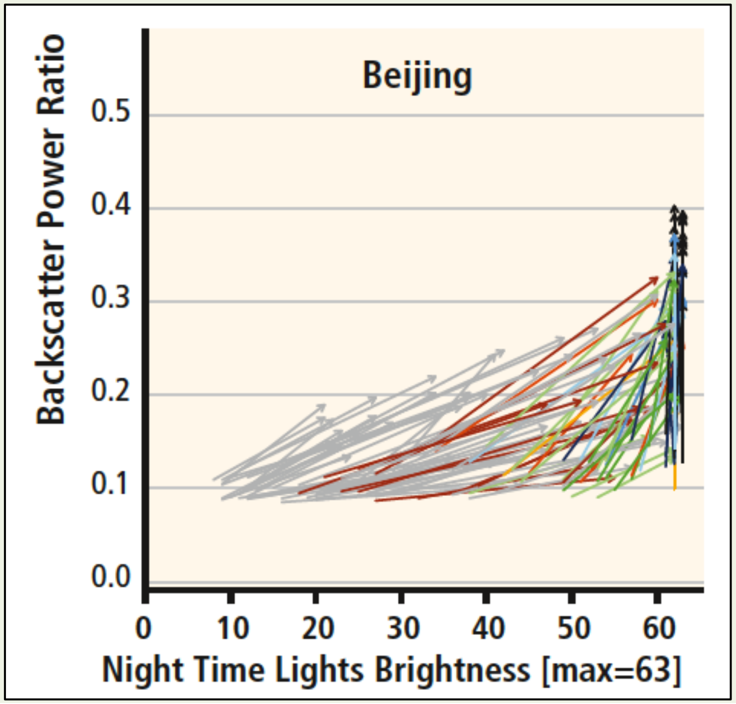


Fig. 1 Different sublayers of an urban boundary layer (following the classification of Oke 1988)

Wang, Li, et al. 2013. *Boundary-Layer Meterol*.



What is impact on modeled urban temperatures (air and radiative; day and night) of building height changes in central Beijing during 2000-2010?

Conclusions

- Ongoing mapping of global urban expansion 2000-2010.

- Daytime cooler areas in urban core can occur not only with high vegetation cover, but also with structure-derived shading.

- Rapid building development in urban core of large cities does not lead to changes in MODIS LST (day or night, TERRA or AQUA).

Extra slides

International Journal of Remote Sensing, 2015
Vol. 36, No. 2, 665–679, http://dx.doi.org/10.1080/01431161.2014.999883

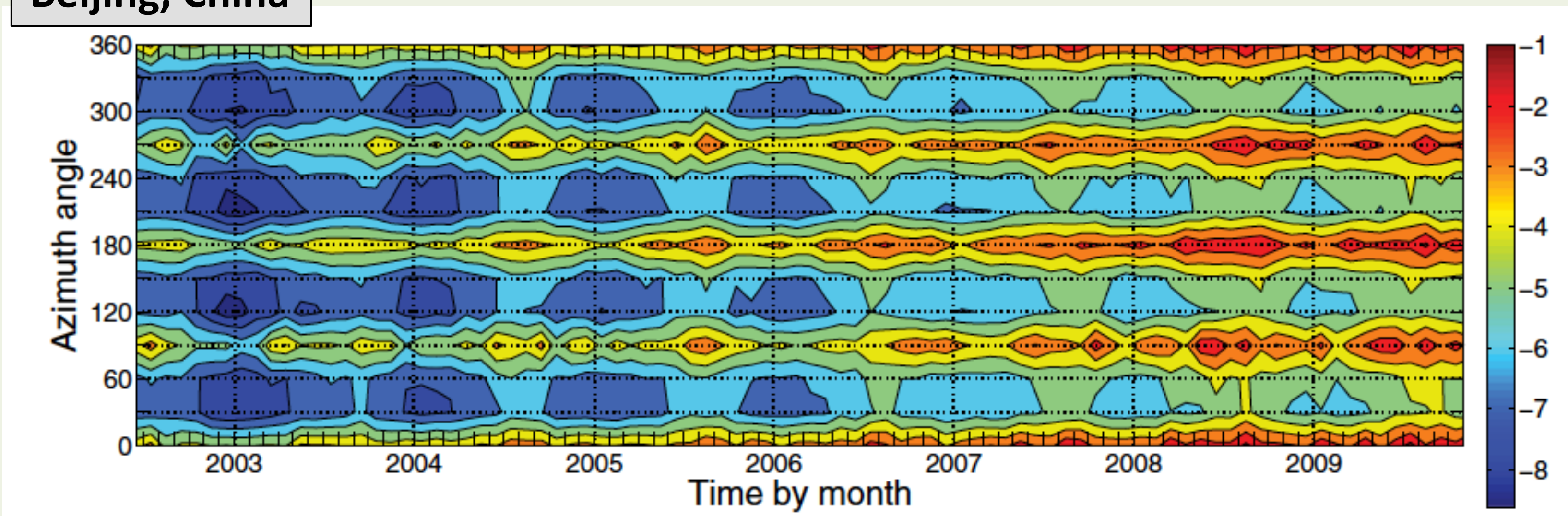
Taylor & Francis
Taylor & Francis Group

Satellite radar anisotropy observed in urban areas

Aaron C. Paget[a]*, Steve Frolking[b], David G. Long[a], and Tom Milliman[b]

Hovmöller diagrams of time series of monthly mean (x-axis) of the 30° binned (y-axis) QuikSCAT Level 1B σ^0 HH data (in dB).

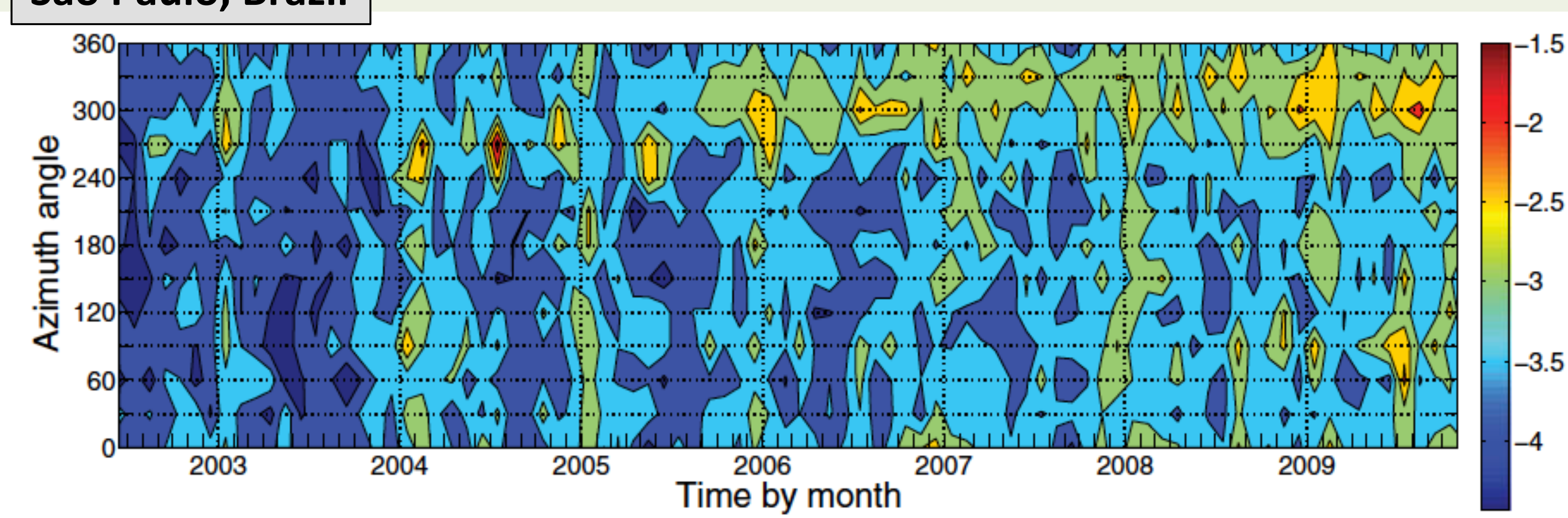
Beijing, China



Beijing:

- strong increase over time.
- strong azimuthal asymmetry.

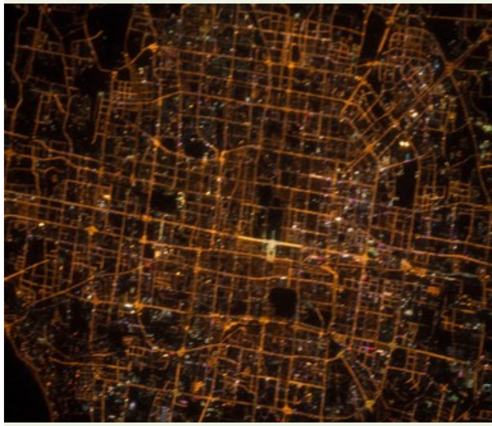
São Paulo, Brazil



São Paulo:

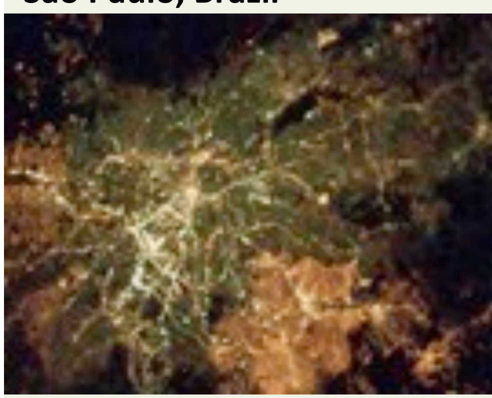
- weaker increase over time.
- weak azimuthal asymmetry.

Quikscat level 1b backscatter



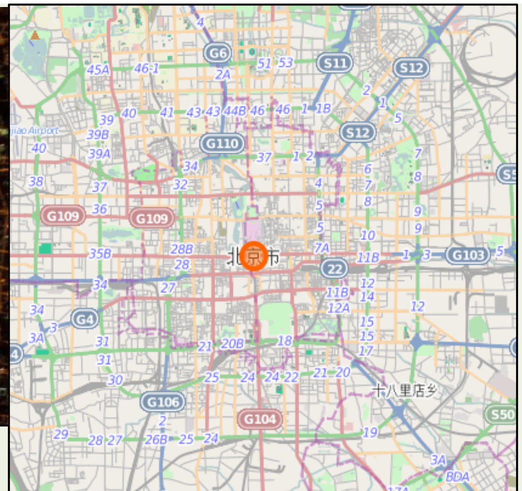
Beijing, China

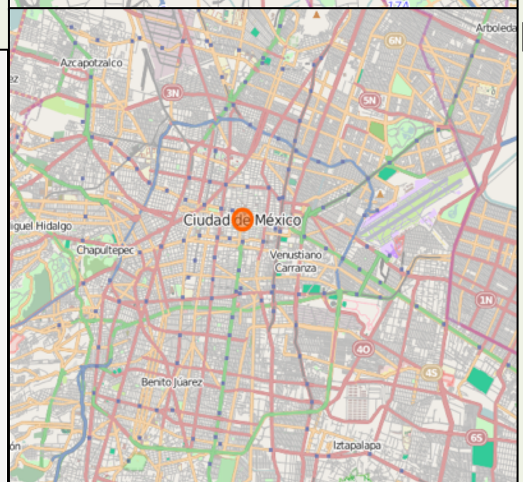
photos from ISS

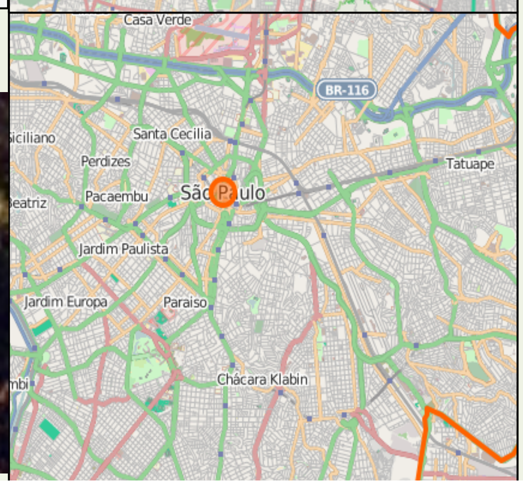


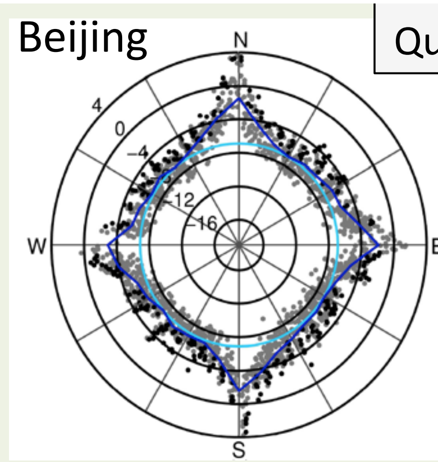
São Paulo, Brazil

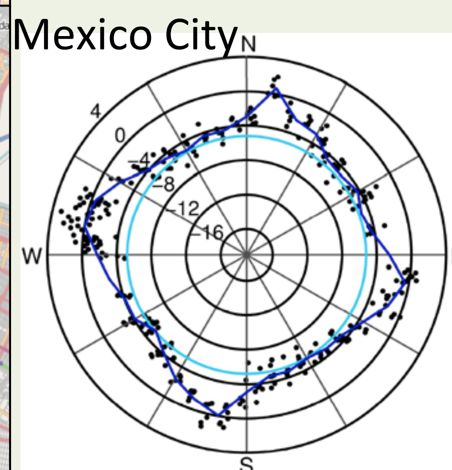
www.OpenStreetMap.org

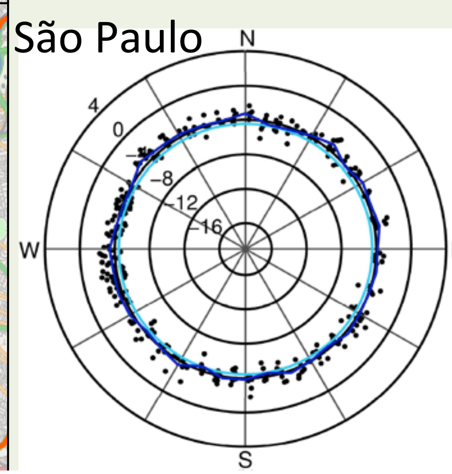








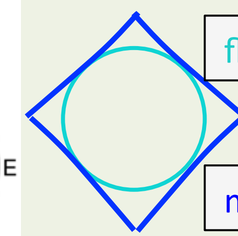




Azimuthal dependence of individual backscatter returns vary by city (high to none).

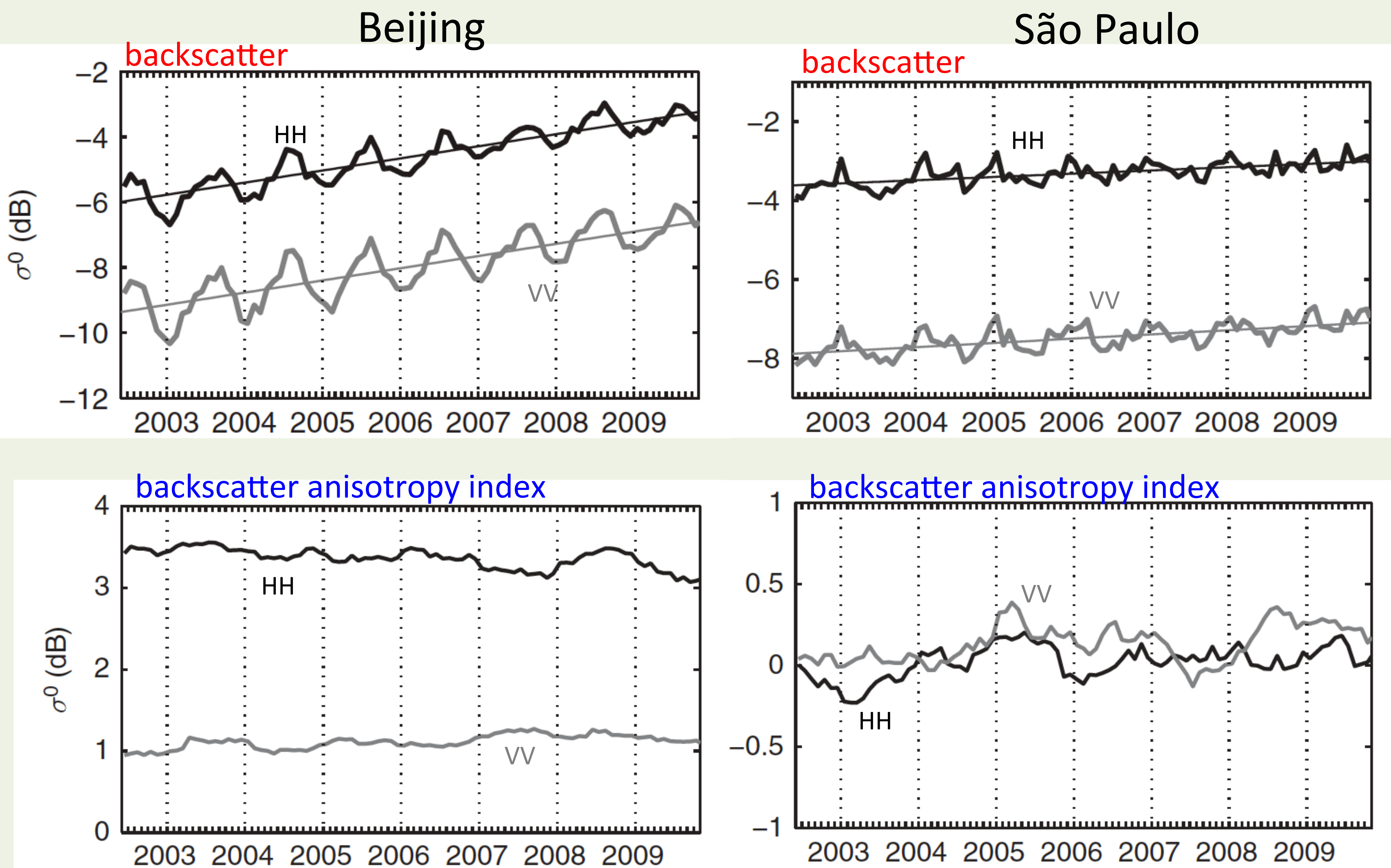
Seems to be strongly correlated with orientation of major urban road networks.

Averaging over one or more months fully samples azimuthal range.



Paget et al. 2015 *IJRS*

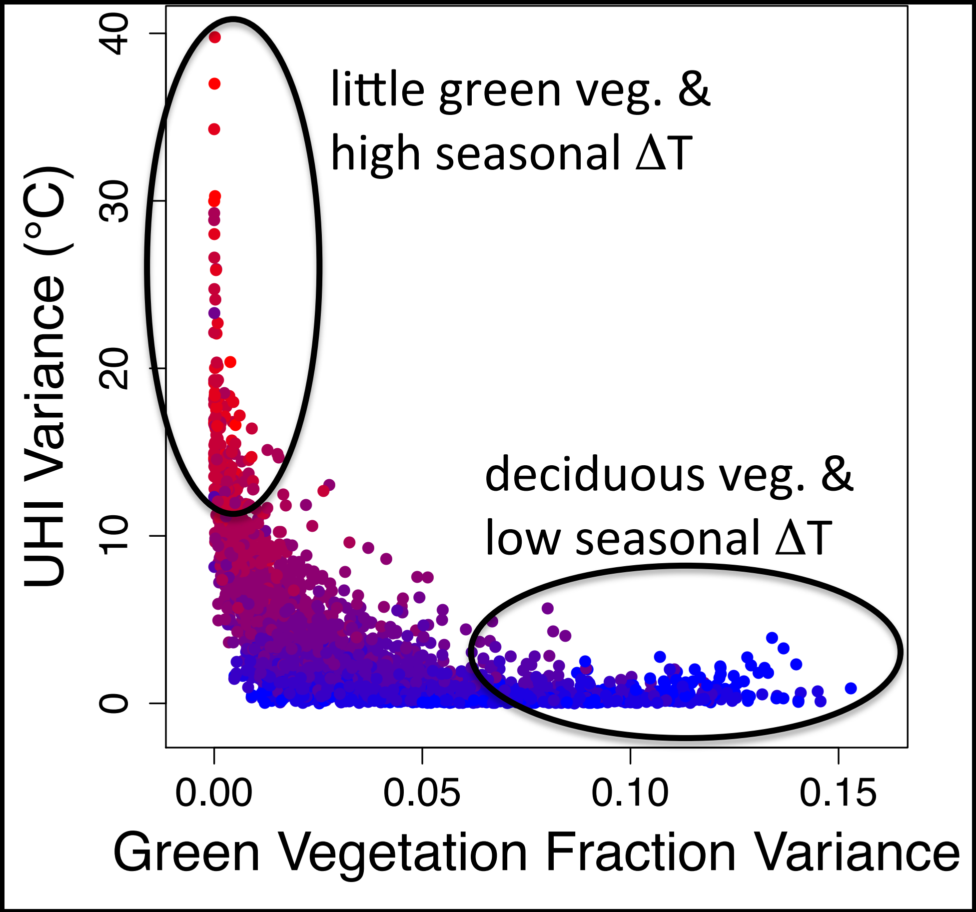
Although urban backscatter magnitude changed over 1999-2009, there was no trend in azimuthal dependence for several large cities we sampled.



Paget et al. 2015 *IJRS*

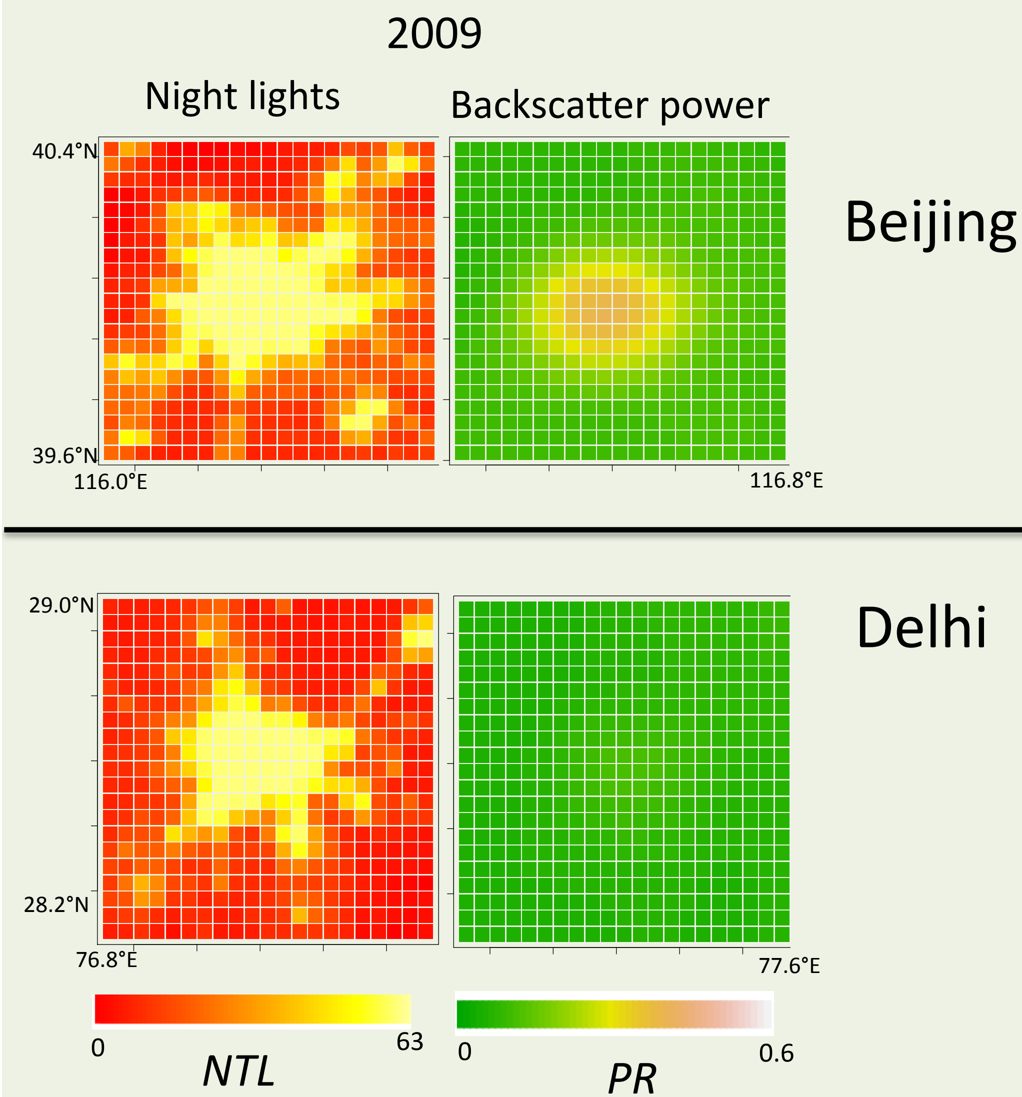
Urban Heat Island ~ Spectral Mixture Analysis

Seasonality of ΔT increases as pixel fraction of green vegetation decreases.



L. Cheek & M. Friedl, BU

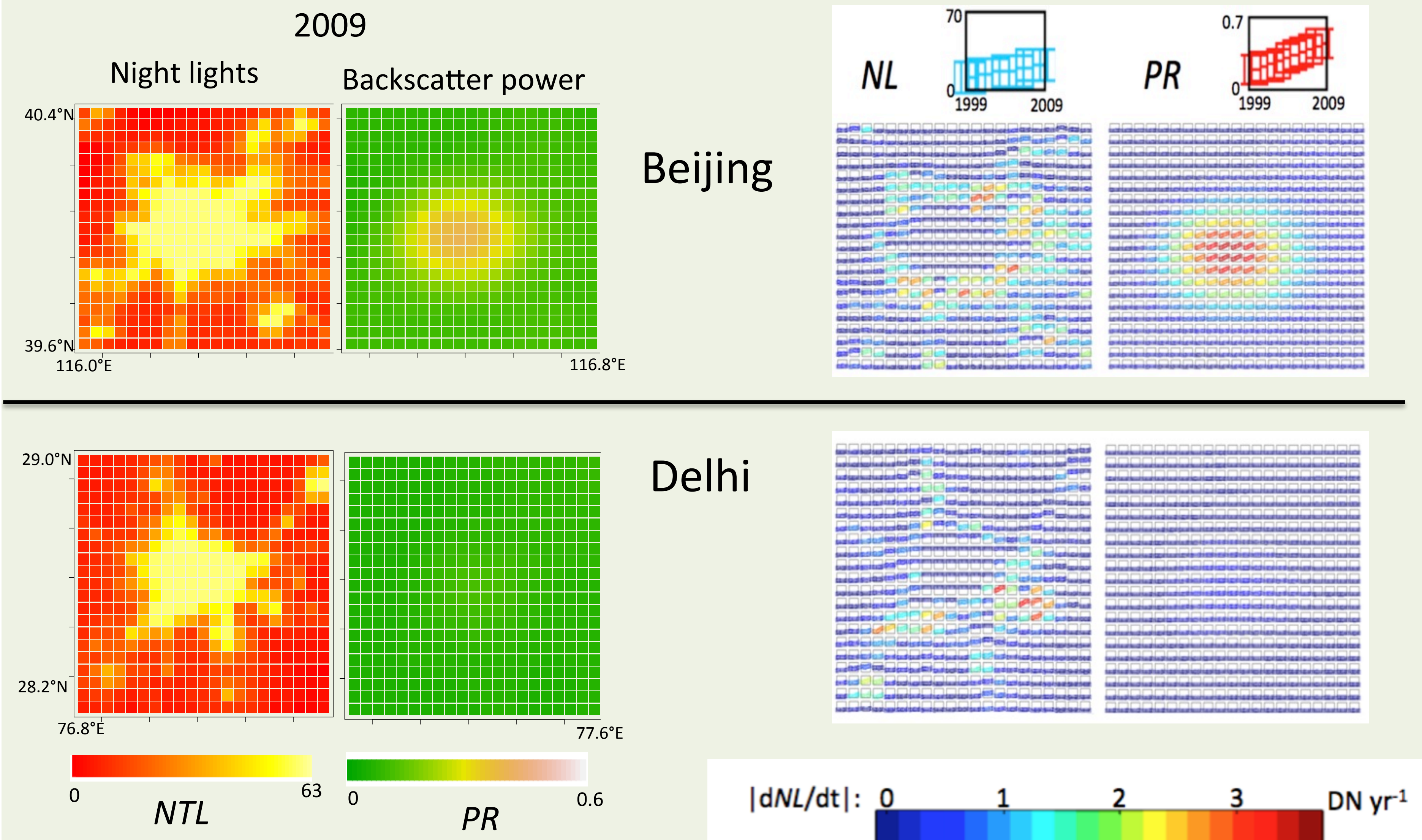
Night lights & backscatter – different urban characteristics.



Plan view: 21x21 grid cells (0.05°)

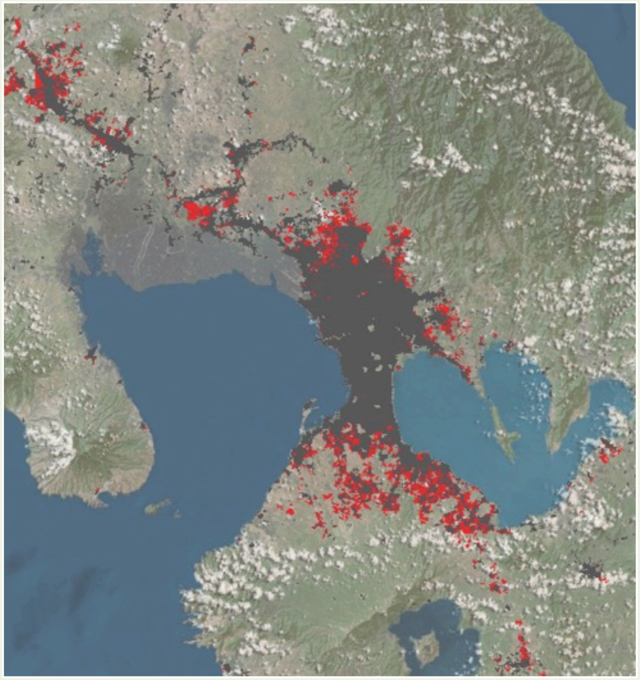
Frolking et al. 2013 *ERL*

Night lights & backscatter – different urban characteristics & modes of change.

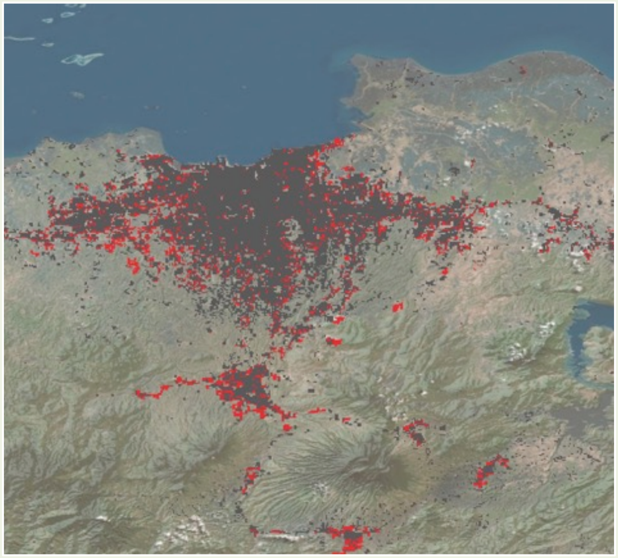


Plan view: 21x21 grid cells (0.05°)

Frolking et al. 2013 *ERL*



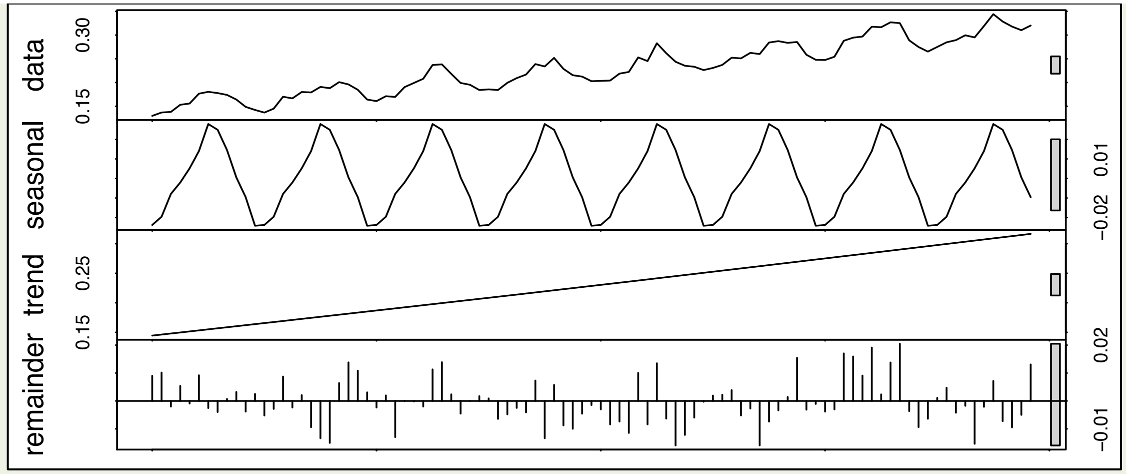
Manila, Philippines



Jakarta, Indonesia

Beijing 2002-2009: monthly data trends

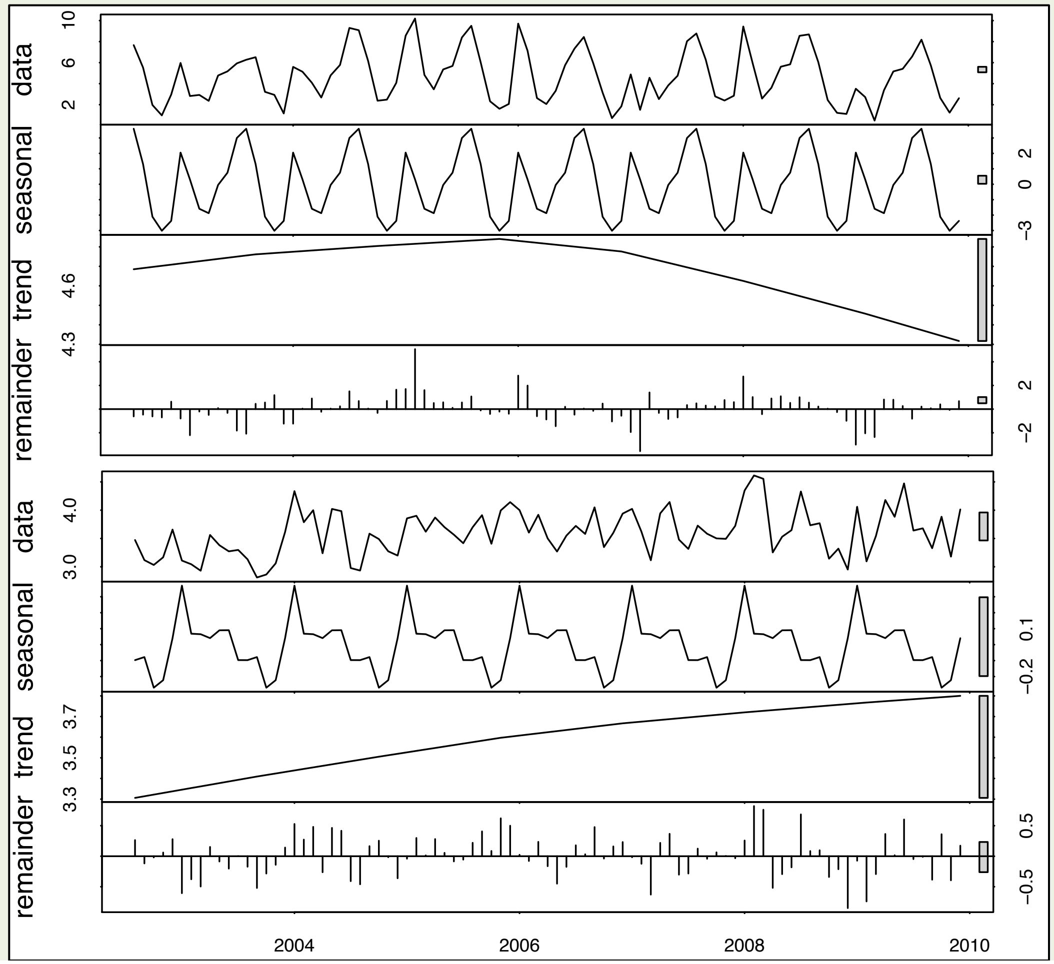
Quikscat backscatter



Seasonal Decomposition of Time Series by Loess in R (‘*stl*’)

daytime urban core – rural UHI (ΔT in °C)

nighttime urban core – rural UHI (ΔT in °C)



Strong trend in QScat

Weak trends in UHI

Hypothesis not supported.